FOOD SECURITY IN INDIA

BY

ADITYA SHRINIVAS

DISSERTATION

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Doctoral Committee:

Associate Professor Kathy Baylis, Co-Chair
Assistant Professor Ben Crost, Co-Chair and Director of Research
Associate Professor Mindy Mallory
Assistant Professor Hope Michelson
Professor Prabhu Pingali, Cornell University

Abstract

This thesis examines the role of social safety nets in providing food security and income stability in developing economies. The first two chapters study the effectiveness of one of the world's largest safety net program - India's Public Distribution System (PDS). The first chapter examines the impact of the program on the labor market. The second analyzes the effect of the program on food security. The third chapter asks whether households fully smooth consumption in the face of fluctuations in income.

In the first chapter (co-authored with Kathy Baylis and Ben Crost), we examine the effect of the PDS program on labor supply and wages. Our empirical analysis exploits changes in the generosity of this in-kind transfer brought about by India's National Food Security Act in 2013. Using detailed data on transfer eligibility, labor supply and wages, we find that larger transfers led to lower labor supply and higher wages, and that these effects particularly benefited the poor. The wage increases from the recent expansion account for 30% of the total welfare gains for the poorest quintile. Further, the effect on labor supply and wages is particularly strong in years with bad productivity shocks. Our results suggest that social transfers can have an additional poverty-reducing effect through the wage channel, and can play an important role in preventing the vicious cycle of low wages and high labor supply that afflicts poor households in bad years.

In the second chapter (co-authored with Kathy Baylis, Ben Crost and

Prabhu Pingali), we examine the effect of the PDS program on household consumption and nutrition. We find that increased PDS subsidies, that resulted from the National Food Security Act in 2013, improved nutrition and "crowded- in" the consumption of nutritious non-staple foods along with increasing calories. Further, the subsidy supported food consumption as opposed to flowing to other goods. PDS beneficiaries consumed 84% of the transfer value in the form of food, suggesting that the subsidy did not cause them to substantially reduce their consumption of non-subsidized food. The effect of PDS subsidies on food consumption is highest in households where women have more control over the food budget, suggesting a role of intra-household bargaining. Overall, our results suggest that in-kind staple food subsidies can lead to large improvements in nutritional outcomes of poor households.

In the third chapter, I study whether informal risk-sharing can provide full consumption insurance in village economies. I propose a new test for full risk sharing that accounts for heterogeneity in risk and time preferences, and apply this method to Indian village data. While there is substantial and significant heterogeneity in estimated risk and time preferences, full risk sharing is rejected for both cases - with and without heterogeneity. Estimated risk and time preferences are associated with wealth and household characteristics, suggesting an incomplete separation between consumption and production, a characteristic of incomplete markets.

To my parents

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INTRODUCTION

Agricultural households in village economies live in poor and high-risk environments. Per-capita consumption and per-capita income is low and the risk to income from drought, floods, crop failure and illness is high. Households who fail to insure themselves against such income shocks may experience consumption fluctuations with detrimental effects on household welfare. The protection of households from such income shocks depends on the availability and effectiveness of the existing risk-bearing institutions.

This thesis examines the effectiveness of two forms of risk-bearing institutions - social safety nets and risk pooling. Safety nets serve to provide assistance to the poor and protect the vulnerable. About 2.5 billion people world-wide are covered by safety nets, of which 36% of the very poor escaped extreme poverty. In addition to relying on safety nets, households use many ex-post and ex-ante strategies to keep their consumption smooth in the face of income risk. Storage, accumulation of assets and diversification of crops may be some of the ex-ante means of reducing risk. There may also be ex-post means of coping with risk through informal mutual agreements of pooling income within a village. Such informal pooling of risk may potentially provide complete insurance against income shocks. In order to fully assess the vulnerabilities of households in village economies, where formal credit markets are incomplete or non-existent, it is important to understand how well households' consumption is smoothed.

This thesis poses a simple question: How good or how bad are these institutions in providing food security, income stability and consumption insurance. In the first two chapters, I study whether social safety nets provide food security and income stability. The third chapter analyzes consumption smoothing and whether informal risk pooling can provide full consumption insurance in the face of income risk.

The setting of this dissertation is in rural India. Among the developing countries, India presents a compelling case for studying safety nets, with the highest number of poor people in the world as of 2015 and more spending on safety nets than most developing countries. Further, a majority of the population in Indian villages rely on agriculture as the basis of their livelihood and are vulnerable to adverse risks from erratic monsoon. Various policy issues turn on this level of risk and on the presence or absence of risk reduction mechanisms. First, are the poor secure in food and nutrition? Second, can the landless laborers break away from the vicious cycle of high labor supply and low wages caused by adverse shocks? Third, does uninsured risk cause fluctuations in consumption? In short, is there some scope for policy or policy reform? In this dissertation, I present research on these critical policy questions using detailed household and individual level data from ICRISAT's "Village Dynamics in South Asia" panel between 2010 and 2015.

In the first two chapters, I study the labor market and nutritional impact of India's largest social safety net - The Public Distribution System. The PDS provides in-kind transfers of staple food to the poor at a highly subsidized price. The program is by far India's most important safety net, providing assistance to over 800 million people and accounting for 60% of the social assistance budget. With more than 530,000 fair price shops, that cover around 85% of the villages in the country, the PDS is the most far reaching social safety net in India. The efficacy of such a massive program in addressing the persistent problem of malnutrition in India holds important lessons for future food security and social welfare policy both in India and in many other developing countries with similar programs.

More broadly, in-kind transfers - particularly of food - are an important part of social safety nets around the world. Approximately 1.5 billion people worldwide receive in-kind food transfers (Alderman et al., 2018), and about 44% of individuals covered by social safety nets receive in-kind transfers (World Bank, 2015). Despite their importance for developing country safety nets, food transfers have received relatively little attention in the recent economics literature, which has predominantly focused on cash transfers and public works programs (Banerjee et al., 2017; Baird et al., 2018; Imbert and Papp, 2015)

Our empirical strategy exploits changes in the PDS transfers that resulted from the National Food Security Act (NFSA) of 2013. Before this legislation, states had substantial discretion in setting the prices and quantities of PDS rations provided to program beneficiaries. This changed after the passage of the NFSA, which imposed new generous national targets on all states. For instance, states were mandated to provide 5 kg per capita of staple grains to eligible households at prices no higher than 3 Rs/kg for rice and 2 Rs/kg for wheat. States whose pre-NFSA prices or quantities fell short of those targets had to expand their subsidies while states who were already in compliance did not. We combine this policy variation with individual-level data from ICRISAT's VDSA panel between 2010 and 2015. Crucially for our study, the ICRISAT panel contains data on a household's size and the type of PDS ration card it possesses. We combine these data with information on state-level PDS entitlements to generate a precise measure of the value of the PDS transfer a household is entitled to receive at every point in time. This variation lends itself well to estimating the causal effect of the transfer, since it was generated by a national rule and is therefore not likely correlated with changes in local policies or economic conditions.

In Chapter 1, we focus on the labor market effects of PDS. We find that an increase in PDS transfers led to a moderate decrease in labor supply and an increase in the equilibrium wage. A 70 rupee per-capita per month increase in the value of the transfer, equivalent to the average post-NFSA increase in entitlements in the state of Bihar, causes labor supply to decrease by 1.5% or 0.35 days per month. This reduction in labor supply causes daily wages to increase by 4.4% or 10.15 Rs per day. Effects are strongest for non-farm labor and wages, consistent with the notion that poor households use non-farm labor as a coping mechanism. Furthermore, we show that total welfare gains from the PDS are the highest for the poorest quintile, comprising about 13% of household consumption, of which the indirect gain from wage change accounts for 30% of this total.

We further explore whether the labor market effect of the PDS program can stabilize wages against bad productivity shocks. Previous studies have found that poor households increase labor supply to buffer negative shocks, so that wages deteriorate precisely at times when the poor are most dependent on labor income (Kochar, 1999; Jayachandran, 2006; Ito and Kurosaki, 2009; Rose, 2001). By reducing the dependence of poor households on labor income, PDS transfers might have particularly beneficial labor market effects in years with bad economic shocks. Consistent with this intuition, we find that the effect of PDS transfers on labor supply and wages is particularly large during years with late monsoon onset, a rainfall shock associated with reduced agricultural production. This result suggests that in-kind food transfers can play an important role in preventing the vicious cycle of low wages and high labor supply that afflicts poor households in bad years.

In Chapter 2, we focus on the impact of PDS on household consumption and nutrition. We find that increases in the PDS subsidy substantially improve nutrition. In addition to increasing consumption of staple cereals, PDS subsidies crowd-in consumption of diverse food types including pulses, milk and milk products, oils, sugar, fruits and vegetables. Consequently, the PDS subsidy increases overall calorie, protein and fat intake. A 100 rupee (monthly) increase in subsidy, equivalent to the PDS increase in the state of Karnataka in 2013, translates to around 17% increase in energy and protein intake, 10% increase in fat intake. We find that PDS beneficiaries consume 83% of the subsidy value in the form of food, suggesting that the transfer does not cause them to substitute away from non-subsidized food. The main policy implication from this study is that food subsidies still remains an effective tool in improving nutrition and can lead to large improvement in nutritional outcomes of poor households.

In Chapter 3, I study whether informal risk-sharing can provide full consumption insurance in village economies. Households in village economies are generally not completely insured—income and consumption are typically found to be positively correlated. Several explanations have been proposed for the failure of full insurance, including moral hazard, limited commitment and hidden income. An emerging strand of literature suggests that ignoring heterogeneity in preferences may explain rejections of full risk sharing.

I propose a new test for full risk sharing that accounts for heterogeneity in risk and time preferences, and apply this method to Indian village data. While there is substantial and significant heterogeneity in estimated risk and time preferences, full risk sharing is rejected for both cases - with and without heterogeneity. Estimated risk and time preferences are associated with wealth and household characteristics, suggesting an incomplete separation between consumption and production, a characteristic of incomplete markets.

CHAPTER 1

LABOR MARKET EFFECTS OF SOCIAL SAFETY NETS : EVIDENCE FROM INDIA'S PUBLIC DISTRIBUTION SYSTEM

1.1 Introduction

Developing countries have substantially increased their expenditure on social safety nets over the past two decades. Recent estimates suggest that social safety nets, including cash transfers, public works programs and in-kind transfers, cover over 2.5 billion people in developing countries and have helped 36 percent of the poorest escape poverty (World Bank, 2015; Alderman et al., 2018).[1] Despite their popularity and proven gains, the labor market effects of safety nets - particularly social transfers - have long been a central concern for policy makers and the public at large. Standard economic theory suggests that social transfers reduce labor supply through an income effect. Alternatively, social transfers may increase labor supply by helping the poor overcome credit constraints or by improving their health productivity (Baird et al., 2018). As these programs expand in developing countries, we need to understand their effect on their target population, including their effect on labor supply and resulting welfare.

Even if safety nets affect labor supply, it is not clear how this change in labor supply affects the poor. In the public debate, a reduction in labor supply by the poor is often framed as undesirable, with references to safety nets acting as "hammocks" for the "lazy poor" (Paul Ryan, quoted in the Huffington Post (2012); Madras High Court, quoted in the Telegraph India (2018)). However, the welfare effects of a reduction in the labor supply of the poor are unclear. A reduction in labor supply could drive up low-skilled wages, improving the welfare of net labor suppliers, who are typically poorer than average. This type of redistributive wage effect can lead to

[1] Social safety nets provide assistance and protection for the poor and vulnerable people and serve to reduce poverty and inequality. The terms "safety nets", "social assistance" and "social transfers" are used interchangeably hereafter.

a substantial reduction in poverty as shown in the case of India's workfare program (Imbert and Papp, 2015; Berg et al., 2012). Recent studies suggest that the poverty-reducing effects of social assistance programs can be substantially underestimated if these general equilibrium effects are not taken into account (Cunha et al., 2011; Muralidharan et al., 2017).

In this study, we examine the labor supply and wage effects of one of the world's largest social safety nets - India's Public Distribution System (PDS). The PDS provides in-kind transfers of staple food to the poor at a highly subsidized price. The program is by far India's most important safety net, providing assistance to over 800 million people and accounting for 60% of the social assistance budget. More broadly, in-kind transfers - particularly of food - are an important part of social safety nets around the world. Approximately 1.5 billion people worldwide receive in-kind food transfers (Alderman et al., 2018), and about 44% of individuals covered by social safety nets receive in-kind transfers (World Bank, 2015). Despite their importance for developing country safety nets, food transfers have received relatively little attention in the recent economics literature, which has predominantly focused on cash transfers and public works programs (Banerjee et al., 2017; Baird et al., 2018; Imbert and Papp, 2015)

Our empirical strategy exploits changes in the PDS transfers that resulted from the National Food Security Act (NFSA) of 2013. Before this legislation, states had substantial discretion in setting the prices and quantities of PDS rations provided to program beneficiaries. This changed after the passage of the NFSA, which imposed new generous national targets on all states. For instance, states were mandated to provide 5 kg per capita of staple grains to eligible households at prices no higher than 3 Rs/kg for rice and 2 Rs/kg for wheat. States whose pre-NFSA prices or quantities fell short of those targets had to expand their subsidies while states who were already in compliance did not.[2] In addition, the NFSA mandated that states calculate PDS rations on a per-capita basis, allocating 5 kg of subsidized grain per eligible household member. Before the NFSA, some states had calculated rations on a per-household level, allocating 20-25 kg of grain to each eligible household, regardless of size. These states were forced to switch to a per-

[2]For instance, the state of Bihar reduced its prices for PDS rice from 7 to 3 Rs/kg to comply with the NFSA mandate. In Jharkhand, where the price of PDS rice was already at 1 Rs/kg and therefore in compliance with the mandate, the price remained unchanged.

individual allocation, leading to more generous transfers for large household relative to small ones.

We combine this policy variation with individual-level data from ICRISAT's "Village Dynamics in South Asia" panel between 2010 and 2015. Crucially for our study, the ICRISAT panel contains data on a household's size and the type of PDS ration card it possesses. We combine these data with information on state-level PDS entitlements to generate a precise measure of the value of the PDS transfer a household is entitled to receive at every point in time. To isolate the variation generated by the NFSA from discretionary state-level changes to PDS entitlements, we implement an instrumental variables approach based on counterfactual entitlements that would have existed if states had expanded PDS by the bare minimum needed to comply with the NFSA mandate. This variation lends itself well to estimating the causal effect of the transfer, since it was generated by a national rule and is therefore not likely correlated with changes in local policies or economic conditions. The fact that the changes to entitlements caused by the NFSA differed substantially across households in the same village allows us to estimate the effect of PDS transfers while controlling for a wide range of unobserved characteristics through individual, time and village-by-time fixed effects.[3]

We find that an increase in PDS transfers led to a moderate decrease in labor supply and an increase in the equilibrium wage. A 70 rupee per-capita per month increase in the value of the transfer, equivalent to the average post-NFSA increase in entitlements in the state of Bihar, causes labor supply to decrease by 1.5% or 0.35 days per month. This reduction in labor supply causes daily wages to increase by 4.4% or 10.15 Rs per day. These estimates imply an elasticity of labor demand of 0.38, which is consistent with existing evidence (Imbert and Papp, 2015; Evenson and Binswanger, 1980). Effects are strongest for non-farm labor and wages, consistent with the notion that poor households use non-farm labor as a coping mechanism.

We then analyze the distributional impacts of the wage increases caused by expanded PDS transfers. We show that wage increases redistribute income from richer households, who are net labor buyers, to poorer households, who

[3]For estimates that control for village-by-time fixed effects, identification is effectively based on a triple-differences approach that uses households whose entitlements are unaffected by NFSA, perhaps because they are not entitled to PDS transfers, as an internal control group.

are net labor suppliers. Our estimates suggest that the indirect welfare gains from a 7% wage increase brought about by a 70 rupees increase in PDS transfer value, is highest for the poorest quintile who gain about 118 rupees per household, equivalent to 4% of total household consumption. In total, the direct and indirect gains from the PDS program are again the highest for the poorest quintile, comprising about 13% of household consumption, of which the indirect gain from wage change accounts for 30% of this total.

We further explore whether the labor market effect of the PDS program can stabilize wages against bad productivity shocks. Previous studies have found that poor households increase labor supply to buffer negative shocks, so that wages deteriorate precisely at times when the poor are most dependent on labor income (Kochar, 1999; Jayachandran, 2006; Ito and Kurosaki, 2009; Rose, 2001). By reducing the dependence of poor households on labor income, PDS transfers might have particularly beneficial labor market effects in years with bad economic shocks. Consistent with this intuition, we find that the effect of PDS transfers on labor supply and wages is particularly large during years with late monsoon onset, a rainfall shock associated with reduced agricultural production. This result suggests that in-kind food transfers can play an important role in preventing the vicious cycle of low wages and high labor supply that afflicts poor households in bad years.

Our estimates provide novel evidence for the labor market effect of social safety nets, based on plausibly exogenous, household-specific variation in benefits. The most closely related previous evidence comes from Sahn and Alderman (1996) who examine the labor supply effects of Sri Lanka's program of subsidized rice transfers using cross-sectional data and an instrumental variables approach that instruments subsidy levels with household characteristics such as asset ownership and house size.

Our results differ from the literature on labor market effects of social transfer programs in developed countries. Studies in this have generally found very small if any work disincentives of the United States' food stamp program (Hoynes and Schanzenbach, 2012; Currie, 2003; Fraker and Moffitt, 1988; Hagstrom, 1996), Medicaid program (Gruber, 2000; Buchmueller et al., 2015) and housing programs (Jacob and Ludwig, 2012; Collinson et al., 2015). Our results suggest that this evidence does not necessarily generalize to a developing country context, where poor households are much closer to subsistence levels and food makes up a large part of their total expenditure.

At first glance, our results also contrast with recent evidence that cash transfers have no consistent negative effects on labor supply in developing countries (Banerjee et al., 2017; Jones and Marinescu, 2018; Salehi-Isfahani and Mostafavi, 2016). However, our estimates suggest a very modest effect on labor supply that cannot be ruled out by most studies of cash transfers. For example, the 95% confidence interval of the effect of a cash transfer, worth 10% of household consumption, on hours worked, estimated by Banerjee et al. (2017) includes a reduction of not more than 6%. Thus, our estimate of about 2% labor supply reduction for a transfer of similar magnitude, is well within their confidence interval. It is only because of inelastic labor demand that we find that this small reduction in labor supply has a large effect on local wages, and thus, local incomes. It is, of course, also possible that cash and in-kind transfers may not be equivalent with respect to their labor supply effects.[4] While the issue of cash versus in-kind delivery of safety nets has recently received considerable attention (Gentilini, 2016; Blattman et al., 2017), it is beyond the scope of this paper, since the absence of a cash-transfer program in India during our study period makes it impossible for us to compare the two delivery modes.

Finally, our results suggest that the labor market effects of in-kind food transfers are similar to those of public works programs, which have been found to have considerable effects on labor supply in the private sector and consequently on equilibrium wages (Imbert and Papp, 2015; Berg et al., 2012; Muralidharan et al., 2017).

Our study also contributes to the literature on wage determination in rural labor markets in developing countries (Kochar, 1999; Jayachandran, 2006; Kaur, 2014). We show that large increases in the in-kind food transfers can raise wages for casual low-skilled workers in the private sector. Transfers can thus improve the welfare of the poor through a labor market effect in addition

[4] There are several reasons why labor supply effects of in-kind food may be different than cash. First, labor supply will necessarily be lower under in-kind transfer, as compared to cash, if the in-kind transfer is infra-marginal and if there is strong complementarity between the in-kind good and leisure (Gahvari, 1994; Munro, 1989; Leonesio, 1988). Moreover, the stronger disincentive effect of in-kind transfer on labor supply holds, even if leisure and the subsidized good are substitutes or if the two are independent (neither complements nor substitutes), as long as the infra-marginal effect more than offsets the substitution effect. Second, recent studies have shown that households do not treat food as fungible due to role of intra-household bargaining (Breunig and Dasgupta, 2005) or mental accounting (Hastings and Shapiro, 2018).

to their direct effect on food consumption and nutrition. Our results also highlight the importance of accounting for local general equilibrium effects in program evaluation (Acemoglu, 2010). Ignoring the general equilibrium effects on labor market would lead us to underestimate the impact of the PDS program on the welfare of the poor.

Credible estimates of the benefits of the PDS program are particularly valuable in light of the Indian policy debate around the effectiveness of the program. Proponents have argued that PDS should be expanded as it improves welfare of the poor by improving their food security. Critics have objected on the grounds that the program is poorly targeted and may have little impact on nutrition. Our results suggest that, despite its well-known problems of high costs and leakage, PDS subsidies generate substantial indirect benefits for the poor through the labor market, which have so far received little attention in this debate.

1.2 Public Distribution System of India

The Indian Public Distribution System (PDS) is the world's largest in-kind food transfer program. It is the largest social safety net program in India and accounts for almost 1% of the GDP (approx. 10 billion $US in 2016 Government of India (2017)). The PDS has been in existence prior to India's independence. It was initially established as a rationing system by the British Government during World War II to ensure workers in a few urban centers received food (Nawani, 1994). In the early 1970s, the program evolved into a welfare program with the primary objective of providing food security to vulnerable households. Since then, the PDS has been the primary policy for food security in India.

In 1997, the Indian central government reformed the PDS from a universal system to a targeted program that supported the poor, using a system of household-level allocations based on ration cards. This system was expanded in 2002 and further reformed by the National Food Security Act (NFSA) in 2013. The PDS is jointly implemented and jointly financed by center and state governments in a way we describe in the next section. We begin by describing the main features of the PDS system in the pre-NFSA period between 2002 and 2013, many of which remained in place after the NFSA. The subsequent section describes the major changes to the PDS system brought about by the NFSA, which form the basis of our identification strategy.

1.2.1 PDS before the National Food Security Act

The PDS is based on a system of ration cards that the government issues to households below the poverty line, which entitle them to receive a set quantity of food grains at a fixed price below the market price. There are two types of ration cards, Below Poverty Line (BPL) and Anthodaya Anna Yojanaa (AAY).[5] BPL cards are targeted to households below the poverty line, while AAY cards are reserved for the poorest among the BPL population who are disadvantaged in other ways, e.g. widows, disabled or elderly.

Ration cards are allocated through a two-step process involving central and state governments. First, the central government determines the number of BPL and AAY households to be covered under the PDS in each state, based on census data. State governments then use proxy means tests to allocate ration cards among their population. For example, during the pre-NFSA period 2002-2013, the central government estimated that the state of Bihar had 6.5 million households below the poverty line, out of which 2.5 million households were determined to be AAY. Accordingly, the state issued 4 million BPL cards and 2.5 million AAY cards based on a proxy means test that consisted of a series of exclusion restrictions (for example, households that owned more than five acres of land or an automobile were ineligible).[6]

Every year, the central government supplies state PDS systems with subsidized grain through an agency called the Food Corporation of India (FCI), which procures rice and wheat from farmers across the country and stores it in government-operated warehouses. The FCI offers grain to states at a uniform subsidized price called the central issue price, up to a maximum quantity that depends on the number of eligible households in the state. In the pre-NFSA period, the central issue price was 5.65 Rs./kg for rice and

[5] There is also a third type of ration card - Above poverty Line (APL) - for households above the poverty line. APL card holders in general do not receive any food grains and food allocation for APL households is on ad-hoc basis. We focus our attention on the ration cards that are entitled to receive PDS rations - BPL and AAY.

[6] States had some flexibility in deciding the precise nature of the proxy means test used to allocate ration cards. For a more detailed account of ration card identification and allocation, see Saxena (2009)

4.15 Rs/kg for wheat for BPL households. The maximum quantity offered to a state was 35 kg of grain per month per household with a ration card.[7] The central issue price and quantity allocations from the center to state remained constant during the pre-NFSA period, for both BPL and AAY card holders.

State governments choose how much grain to buy from the FCI, up to the maximum offered quantity, and distribute it through a network of over 500,000 retail outlets known as fair price shops, each one serving a large village or a cluster of villages. With a fair price shop in almost every village in India, the PDS is the most far reaching of all social safety nets in the country.[8] At the fair price shop, beneficiaries with a ration card are allowed to purchase up to a fixed quantity of food grains at a fixed price.

Before the NFSA, states had substantial discretion over the prices and quantities they offered to ration-card holders at PDS shops. The pre-NFSA variation in entitlements for BPL-card holders across states is presented in Column A of Table (1.1).[9] As shown there, a number of states chose to offer PDS grains at prices below the central issue price.[10] For instance, Jharkhand offered rice to BPL households at a price of 1 rupee per kg. The cost of this additional discount was borne by the state budget, since the revenues of the fair price shops were smaller than the outlays to the FCI. Moreover, states were also free to sell PDS grains at prices above the central issue price. For instance, pre-NFSA, the state of Bihar offered PDS rice to BPL households

[7] For example, since Bihar had 4 million households with BPL cards and 2.5 million with AAY cards, it was entitled to a monthly maximum of 87,500 metric tons of grain for AAY households at a price of 3 Rs/kg for rice and 2 Rs/kg for wheat (2.5 million AAY households * 35 kg), and 140,000 metric tons for BPL households at 5.65 Rs./kg for rice and 4.15 Rs/kg for wheat (4 million BPL households * 35 kg). States were also allowed to issue more ration cards and cover more beneficiaries than the number of households determined to be eligible by the center, by procuring additional food grains from sources other than the FCI. For instance, pre-NFSA, Andhra Pradesh issued 16.2 million BPL ration cards, compared to 4.1 million below poverty-line households identified by the center. Furthermore, some states such as Maharashtra and Orissa use fair price shops to provide food rations to households above the poverty line at a higher price, on an ad-hoc basis, based on the availability of food grains.

[8] In 2011, there were 506,198 PDS ration shops Government of India (2011b) in 597,608 inhabited villages Government of India (2011a). This suggests that as many as 85% of Indian villages were covered under the PDS. The coverage has since increased. In 2016, there were 532,000 FPs Government of India (2016)

[9] Information on state-level PDS policies before and after NFSA comes from personal fieldwork and government records.

[10] This was only true for BPL households. For AAY households, the central government mandated that states had to sell the full allocation of 35 kg per household at a price no higher than the central issue price.

at a price of 7 Rupees per kg. Quantity entitlements of PDS grain also varied across states. As show in Table (1.1), two states calculated entitlements at the individual level (Andhra Pradesh and Karnataka), while the rest calculated them at the household level. Furthermore, some states had substantially more generous entitlements than others. For example, Jharkhand allocated 35kg of PDS grain to BPL households, while Gujarat only allocated 18kg.

1.2.2 National Food Security Act

In 2013, the Indian central government, passed the National Food Security Act (NFSA), which guaranteed a minimum quantity of food grains at affordable prices to every eligible person in India (NFSA, 2013). The NFSA, labelled as the biggest ever expansion of "right to food" in the world, converted the food grains provided through the PDS into a "legal entitlement" for beneficiaries. As a commitment towards the NFSA, the central government increased the outlays on food subsidy by as much as 25% (or 230 billion rupees) from the previous fiscal year (Government of India, 2014) and substantially increased the generosity of PDS subsidies. The NFSA's main provision was to reduce the central issue price to 3 Rs/kg for rice and 2 Rs/kg for wheat, and to increase the quantity offered to states to 5 kg per eligible individual.

Crucially, the NFSA mandated the prices and quantities at which state governments had to provide PDS rations to beneficiaries - 5kg of food grains per person per month at a price not exceeding 3 Rs/kg for rice and 2 Rs/kg for wheat. This mandate essentially forced states to pass through central issue prices and quantities to beneficiaries; states that implemented NFSA no longer had the option of providing smaller quantities or selling at higher prices than the NFSA mandate. As a result, states whose pre-NFSA entitlements were less generous than the NFSA mandate had to expand their entitlements. States that found themselves already in compliance with the mandate, were free to keep their entitlements unchanged. Our empirical strategy exploits the variation generated by the forced compliance with the NFSA mandate.

Column B in Table (1.1) shows state-level PDS price and quantity entitlements for BPL card holders after the implementation of NFSA. One complication for our analysis is that the renewed political focus on food security, made a number of states expand their PDS entitlements beyond the level necessary to comply with the mandate. These expansions were initiated during state-elections as part of election promises directed towards gaining the support of the poor. For instance, the first executive decision by the Chief Minister of Karnataka in 2013 was to introduce Karnataka's own PDS program "Anna Bhagya Yojana", fulfilling an election promise of reducing the price of PDS rice to Rs 1/kg (Deccan Herald, 2013b). Similarly, the chief minister of Madhya Pradesh introduced the "Mukhyamantri Annapurna Scheme" as part of his election manifesto, and reduced the price for PDS rice to Rs. 1/kg (Deccan Herald, 2013a)

One concern is that these voluntary expansions that occurred during states-elections could bias our estimates by introducing correlation between PDS entitlements and unobserved determinants of labor market behavior. To address this concern, we use an instrumental variables approach that uses the national NFSA mandate as an instrument for the state-level policies. In particular, we construct counterfactual entitlements that would have existed if every state had expanded PDS just enough to comply with NFSA mandates. Column C in Table (1.1) shows the counterfactual entitlements based on minimum compliance with the mandate. In the following two sections, we explain the variation generated by the NFSA price and quantity mandates, and describe how we constructed counterfactual entitlements that isolate this variation.

Variation generated by the NFSA price mandate

Figure 1.1 shows time-series of the PDS rice prices offered to BPL households by the eight states in our data. Pre-NFSA, states had substantial discretion over the prices offered to beneficiaries and a number of states offered prices above the central issue price. Post-NFSA, the center reduced the central issue price from 5.65 Rs./kg to 3 Rs/kg and mandated the states to offer PDS rice at Rs. 3/kg. As a result, states that were out of compliance were forced to bring down prices to comply with the NFSA mandate. For instance, the states of Bihar and Maharashtra reduced their prices from 7 Rs/kg and 6 Rs/kg to the mandated price of 3 Rs/kg. The figure shows that the price mandate was binding; by the beginning of 2014 all states had reduced their

PDS rice prices to 3 Rs/kg or less.

Figure 1.1 also shows that most states that were already in compliance with the mandate continued with their existing entitlements. For instance, Jharkhand and Andhra Pradesh, whose PDS rice price was already below the new mandate at 1 Re/kg, left the price unchanged. An exception is the state of Karnataka, whose pre-NFSA rice price was Rs. 3/kg and therefore in compliance with the mandate. Nevertheless, Karnataka voluntarily reduced its PDS rice price to 1 Re/kg. The figure further shows that some states that were initially out of compliance with the mandate expanded their entitlements more than necessary to reach compliance. For instance, Madhya Pradesh reduced its PDS rice price from 4.5 Rs./kg to 1 Re/kg., even though a reduction to 3 Rs./kg would have sufficed to comply with the mandate.

As mentioned above, we are concerned that voluntary expansions of the type observed in Karnataka and Madhya Pradesh might be correlated with local economic shocks. To address this concern, we use an instrumental variables approach that uses the national NFSA mandate as an instrument for the state-level policies. To isolate the variation generated by the price mandate, we construct counterfactual price entitlements that would have existed if every state had expanded PDS just enough to comply with the NFSA mandate. For this counterfactual, we assume that states in compliance with the price mandate, such as Jharkhand and Andhra Pradesh, made no changes to PDS prices. We further assume that states that voluntarily lowered their prices beyond NFSA targets, such as Madhya Pradesh and Karnataka, only did the bare minimum to comply with the mandate. We also assume that all states complied with the mandate in June 2013, when NFSA was officially enacted, ignoring state-level variation in the timing of the reform's implementation. Figure 1.2 shows actual PDS price entitlements (left) and the counterfactual NFSA target price (right).

Variation generated by the NFSA quantity mandate

A second source of variation for our instrument comes from the NFSA's mandate that states provide at least 5kg of PDS grain per individual in eligible households. As shown in Table (1.1) Column A: Pre-NFSA, states followed different methods to calculate quantity entitlements. Some states, such as Andhra Pradesh and Karnataka offered PDS rations on a per-individual basis while imposing a maximum ceiling per household. Other states, such as Bihar and Maharashtra offered PDS rations on a per-household basis, regardless of size. To compare quantity entitlements across states, we express them in per capita terms, using the state-specific average household size from the census data. Figure 1.3 shows how per capita entitlements evolved over time in the eight states in our sample.

As shown in Column A, five of the six states whose per capita quantity entitlement was initially below 5kg raised their entitlement to comply with the NFSA mandate of 5kg/individual. The exception is Gujarat, which brought its quantity entitlement in line with the NFSA mandate in 2016, after the end of our period of observation. The two states, Jharkhand and Orissa, whose quantity allocation already exceeded 5kg per capita, left their entitlements unchanged.

As with the price mandate, several states expanded their entitlements beyond the level necessary to comply with the NFSA mandate, specifically Karnataka and Andhra Pradesh. As before, we construct counterfactual PDS entitlements that ignore these voluntary expansions beyond the NFSA mandate. Thus we assume that states that voluntarily increased their quantity entitlements beyond the NFSA target level, such as Karnataka and Andhra Pradesh, instead did the bare minimum to reach compliance (Column B in Table 1.1). To construct these counterfactuals, we assume that all states whose pre-NFSA entitlements were below 5 kg per capita changed their entitlement to 5 kg per individual. States whose entitlements were already above 5 kg are assumed to have left their entitlements unchanged.[11] An additional complication comes from the fact that the NFSA mandated 5 kg of grains per individual, but let states decide how this total would be split between rice and wheat. To calculate our counterfactual entitlements based on compli-

[11]It should be noted that the two states whose average per capita entitlements exceeded 5kg calculated the entitlement per household, regardless of size. These states therefore did not comply with the 5 kg per individual mandate for every household. For example, Jharkhand allocated 35 kg per household, so that an household of 8 would receive only 4.4 kg per individual. Nevertheless, the central government allowed these states to keep their entitlements unchanged, effectively treating them as in-compliance with the NFSA mandate, and our definition of the counterfactual entitlements reflects this. To test robustness to this definition of compliance with the mandate, we construct an alternative set of counterfactual entitlements, for which we assume that all states changed their quantity entitlements to 5 kg per individual. Estimates based on this counterfactual instrument are reported in Appendix Table and are very similar to those of our baseline definition of compliance.

ance with the NFSA mandate, we assume that states kept their proportional split between rice and wheat approximately constant as they expanded entitlements. For instance, Bihar's pre-NFSA entitlement was 15 kg/household of rice and 10 kg/household of wheat. We therefore assume that Bihar complied with the NFSA mandate by moving to a post-NFSA entitlement of 3 kg/individual of rice and 2 kg/individual of wheat. For details, see Table 1.1, which shows actual and counterfactual price and quantity entitlements for all states in our sample.

1.3 Data

We use the new wave of ICRISAT's panel study Village Dynamics in South Asia (VDSA). These data contain information on 1300 households with 6000 individuals observed over 60 months from June 2010 to July 2015. The VDSA data cover 30 villages spread across eight states in India: Andhra Pradesh[12], Bihar, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra and Orissa; with 4 villages in each state, except Madhya Pradesh with only 2 villages. The VDSA panel data are geographically divided into 18 villages in the Semi-Arid Tropics (SAT) and 12 villages in the Eastern region of India. The locations of the villages are shown in Appendix figure A4. All the 30 villages have a PDS fair price shop.[13] Households in each village are randomly selected to represent households in four land-holding classes: large, medium, small and landless.

To construct our main outcome variables, we use individual-level data on labor supply and earnings collected every month and individual characteristics such as age and gender collected annually. To identify beneficiary households, we use the ration card status of each household at baseline in 2009. For our estimations, we also use household-level data on rice and wheat consumption and village-level data on rice and wheat prices, collected on a monthly basis.

[12]Two villages are in Telangana, a state formed in 2014. As our dataset begins before the formation of the new state, and for the purpose of consistency, the 2 villages in Telangana are considered as Andhra Pradesh

[13]The corresponding author of this study visited most of these SAT villages in person and conducted extensive fieldwork. The operation of PDS ration shops in each village, validation of ration card status and perception of PDS among beneficiaries were all documented.

Summary statistics are presented in Table (1.2). We drop households with less 48 months of data and households whose head lives outside the village. The final sample consists of 1217 households.

Rainfall data are from the Indian Meteorological Department, defined at a fine spatial resolution of a 0.25 x 0.25 grid cell size. Daily rainfall data for the ICRISAT villages are obtained by mapping the village co-ordinates to each grid cell polygon. No two villages fall within the same grid cell and hence our rainfall measure varies by village. In this study, we consider monsoon onset as a measure for rainfall shock. The first day of the monsoon is defined as the first day after June 1st with more than 20 mm of rain, measured annually for each village. Following Rosenzweig and Binswanger (1993), we measure the timeliness of monsoon onset as the number of days between June 1st and the first day of the monsoon.

1.4 Empirical Strategy

Following Kochar (2005) and Kaul (2018), we quantify the generosity of the PDS transfer by calculating the product of quantity entitlement and price discount (difference between the market and PDS price):[14]

$$T_{hst} = \overbrace{Q_{hst}^{pds\,rice}\left[\overline{P}_{s}^{Market\,rice} - P_{hst}^{pds\,rice}\right]}^{RiceSubsidy} + \overbrace{Q_{hst}^{pds\,wheat}\left[\overline{P}_{s}^{Market\,wheat} - P_{hst}^{pds\,wheat}\right]}^{WheatSubsidy} \tag{1.1}$$

where Q_{hst}^{pds} and P_{hst}^{pds} are the PDS quantity and price entitlements for household h in state s in month t. As described in Section 2, these entitlements are a function of the household's state of residence, ration card status and household size. For each household, we calculate two versions of the transfer value T_{hst}: one based on actual state-level PDS policy at time t, the other based on a counterfactual scenario that isolates the variation induced by the NFSA reform. As described in Section 2, this counterfactual scenario assumes that each state only expanded PDS entitlements by the minimum amount needed

[14]Measuring the generosity of PDS subsidies in terms of their implicit transfer value is valid if the subsidized amount is infra-marginal, so that consumption of staple cereals is more than what is provided by the PDS. Our data suggests that this is generally the case for households in our sample. The average household in our data consumes 48kg of staple cereals as compared to a maximum of 35kg of grains per household provided by the PDS. None of the households get all their staple cereals from the PDS in a given month.

to comply with NFSA mandates, and that all states changed their PDS policy in June 2013, the month when NFSA was passed (see Figures 2 and 3 for a description of actual and counterfactual PDS entitlements). The scenario thus ignores voluntary state-level expansions of PDS and differences in the timing of NFSA reforms, to address the concern that these factors may be correlated with unobserved state-level shocks.

To further address the concern that household characteristics may be affected by state-level PDS reforms or unobserved shocks, we calculate Q^{pds}_{hst} and P^{pds}_{hst} using only household characteristics measured at baseline.[15] Finally, we define the market price, $\overline{P}^{Market}_{s}$, as the average market price in state s before 2013, to avoid endogeneity between market prices and NFSA reforms. [16]. We deflate the PDS transfer value to 2010 Indian rupees and divide by the per-adult equivalent weight of household h.

Figure 1.4 compares our measures of T_{hst} based on actual state policy (left panel) and counterfactual NFSA target policy for a household of six people with a Below Poverty Line ration card. For example, in Bihar before the NFSA reform, this household received 15 kg of rice at 7 Rs./kg and 10kg of wheat at 5 Rs./kg. Market prices were 23 Rs/kg for rice and 14 Rs/kg for wheat, which yields a price discount of 16 Rs/kg for rice and 9 Rs/kg for wheat and a transfer value of Rs.330 (T_{hst}=15*16+10*9). After the NFSA, the same household received 18kg of rice at 3 Rs./kg and 12kg of wheat at 2 Rs./kg, adding up to a transfer value of Rs.504 (T_{hst}=18*20+12*12). Figure 3 shows that there is substantial variation in PDS transfers across states and over time.

1.4.1 PDS transfers reach beneficiaries

We begin by validating that the mandates of the NFSA reform were implemented by the states and that state-level PDS entitlements were in fact available to households. The results of this exercise are presented in Table (1.3). Panel A shows estimated effects of NFSA targets on actual PDS entitlements. Actual entitlements were calculated as described in the previous

[15] Household's ration card status in 2009 and average household size in 2011-12.

[16] Previous studies have shown that food transfers can lower local consumer prices (Cunha et al., 2011). It is therefore possible that an expansion of the PDS transfer leads to a decrease in market prices, since PDS and non-PDS grains are close substitutes, which would bias estimates based on post-expansion market prices

section, by combining baseline household size and ration card status with the current PDS policies of the household's state of residence. NFSA target values were calculated as described in Section 2.2, assuming that all states expanded PDS entitlements just enough to comply with NFSA mandates.

The estimates in Panel A show that states largely implemented the NFSA's mandates. A 1 kg increase in the NFSA quantity target increases a household's actual entitlement by 0.87 kg. Similarly, a 1 Rupee/kg decrease in the NFSA target price reduces the household's PDS price entitlement by 0.69 Rupee/kg. Taking together price and quantity entitlements as described in the previous section, a 1 Rupee increase in the value of the NFSA target increases the actual entitlement value by 0.78 Rupees. The relationship between NFSA target value and actual PDS entitlement is strong, with an F-stat above 200, which allows us to use NFSA targets as an instrumental variable for actual entitlements.

Panel B shows estimates of the effects of changes in PDS entitlements on actual consumption of grains from PDS fair price shops, based on data from the ICRISAT panel. The results show that changes in state-level PDS policies were passed through to beneficiaries. A 1 kg increase in a household's PDS entitlement led to a 0.53 kg increase in consumption of PDS grains. A 1 Rupee/kg decrease in a household's price entitlement reduced the household's purchase price of PDS grains by 0.7 Rupees/kg. Finally, a 1 Rupee increase in the value of a household's entitlement led to a 0.55 Rupees increase in the value of the realized PDS transfer, calculated as the difference between the cost of the household's consumption of PDS grain and the value of the same quantity of grain at current market prices.

Finally, Panel C shows the effect of NFSA targets on actual consumption of PDS grain. As before, the results show that the NFSA targets reached beneficiaries. A 1 kg increase in the NFSA target led to a 0.4 kg increase in consumption of PDS grains. A 1 Rupee/kg decrease in the NFSA target price reduced the household's purchase price of PDS grains by 0.48 Rupees/kg. A 1 Rupee increase in the value of the NFSA target led to a 0.35 Rupees increase in the value of the realized PDS transfer.

Overall, these results show that the NFSA mandates generated substantial variation in state-level PDS policies, as well as household-level PDS entitlements and consumption, which allows us to use the mandates as instrumental variables.

1.5 Results

We examine the impact of PDS on labor supply and wages using the following estimating equation:

$$Y_{ihst} = \alpha_i + \lambda_t + \delta_s t + \beta_1 T_{hst} + \epsilon_{ihst} \tag{1.2}$$

Y_{ihst} is the outcome (labor supply or wages) for individual i in household h, state s, and month t. T_{hst} is the household's PDS transfer value, α_i and λ_t are individual and month fixed effects, and δ_s are state-specific linear time-trends. Standard errors are clustered at the village level. Labor supply is measured as the number of days worked in a month, wages are measured as daily deflated wages in rupees per day. The PDS transfer value T_{hst} is instrumented with its target value based on the NFSA mandates. The PDS transfer value and the NFSA target value is in terms of real per-adult equivalent value in 2010 rupees. We report the results for the full sample of individuals reporting participation in the labor market, and also check that results are robust to restricting the sample to adults aged 18-65.

Table (1.4) reports estimates of the effect of PDS transfers on market labor supply for the full sample of individuals. The results show that a more generous PDS transfer value decreases labor supply. Based on the co-efficient estimates in Column (1), a 1 rupees per-adult increase in PDS transfer value translates to a 0.0073 days per month decrease in individual labor supplied to the market. Results are robust to controlling for village-specific linear time-trends (Column 2), state-specific seasonal month fixed effects (Column 3), state-specific consecutive month fixed effects (Column 4), village-specific consecutive month fixed effects (Column 5). Furthermore, results remain similar with standard errors clustered at the state level (Column 6).

To interpret the significance of the estimate, we consider a policy experiment of increasing the PDS transfer value by 70 rupees per adult-equivalent per month - an amount equivalent to the PDS expansion in Bihar.[17] Based on the co-efficient estimates in column (1), 70 rupees increase in PDS transfer value translates to 0.513 (=70*0.0073) days per month decrease in individual labor supplied to the market. In comparison to the sample mean of 18.9

[17] For a BPL household in our sample, on average, 70 Rupees per adult-equivalent is about 10% of total expenditures and 15% of food expenditures per month

days, the expansion of the PDS program decreases the total individual labor supply by 2.8% (=0.513/18.9).

Table (1.5) reports estimates of the effect of PDS transfers on wages. The results show that a more generous PDS transfer increases the equilibrium wage. Based on the co-efficient estimates in Column (1), a 1 rupees per-adult increase in PDS transfer increases daily market wages by 0.22 Rs/ day. Columns 2-5 show that the wage effect results are robust for more constrained specifications. For a PDS program expansion as in Bihar, the results suggest that, a 70 rupees per-adult increase in PDS transfer value increases daily market wages by approximately Rs 15 (=70*0.211). In comparison to the sample mean, the expansion of PDS program increases daily wages by 7%. This is a large effect for an in-kind food-transfer program. A comparison to the market-wage effect of NREGS, India's public work fare program, shows that our estimate is slightly lower than the estimated 8.9% market-wage increase from the roll-out of NREGS (Imbert and Papp, 2015) and slightly higher than the estimated 6% market-wage increase from improving the implementation of NREGS (Muralidharan et al., 2017).

Table (1.6) separately reports estimates of the effect of PDS transfers on labor supply and wages in the farm and non-farm sectors. The results show that the effect of PDS transfers is concentrated in the non-farm labor market. A 1 rupee increase in transfers increases non-farm labor by 0.0063 days/month, statistically significant at the 10 percent level. The estimated effect of PDS transfers on farm labor is substantially smaller at 0.0015 days/month and not statistically significant at conventional levels. We find a similar pattern for wages. A 1 rupee increase in PDS transfers leads to a 0.18 Rs./day increase in non-farm wages but only a 0.09 Rs/day increase in farm wages. The fact that PDS transfers increase farm wages even though they do not affect labor supply is most likely due to substitution across sectors. Farm and non-farm labor markets are at least partially integrated, so that a decrease in supply of one market leads to an increase in wages in the other.

Our results are consistent with existing evidence that poor households use non-farm income as a coping strategy (Barrett et al., 2001; Ellis, 1998). Since non-farm labor supply is typically the marginal residual labor supply, and therefore more elastic than the supply of farm labor, we would expect that an increase in social transfers will lead households to reduce the former more than the latter.

Our results are consistent with a labor demand elasticity toward the higher end of the range of estimates found in the previous literature. Our estimates above suggest that a 70 Rupees increase in PDS transfers program decreased non-farm labor supply by 1.7% and increased wages by 4.4%. Hence, the elasticity of labor demand is $\tilde{\epsilon_d} = \frac{1.7}{4.4} \approx 0.38$, which is only slightly higher than the 0.31 estimated by Imbert and Papp (2015) and lies within the range of 0.25 to 0.4 estimated by Evenson and Binswanger (1980). for farm employment in India. Of course our estimates reflect the elasticity over the relative short-run, since the period of observation ends two and a half years after NFSA was passed. The long-run elasticity of labor demand is likely to be higher, so that wage effects may be decrease over time.

1.5.1 Robustness Tests

Our empirical strategy is based on the identifying assumption that the labor market outcomes of households whose PDS entitlements increased as a result of NFSA were on parallel trends to the outcomes of households whose entitlements decreased or remained unchanged. The assumption would be violated if these groups of households were on systematically different time-trends, or subject to systematic unobserved shocks that coincide with the implementation of NFSA. We conduct several robustness tests for the identifying assumption.

First, we test for differential pre-existing trends by including a one-year lead of the PDS transfer in our regression.[18] The results, presented in Tables (1.7) and 1.8) show that the coefficient associated with the lead is small in magnitude and statistically insignificant. We thus find no evidence that the labor market outcomes of households whose entitlements were differently affected by NFSA followed different during the pre-NFSA period.

Next, we estimate regressions that control for state-by-time and village-by-time fixed effects, to test whether our results are biased by geographically clustered time-varying unobserved shocks. The most restrictive of these estimates are based on comparing the labor market outcomes of households

[18] As with the contemporaneous transfer value, we instrument the lead with a counterfactual entitlement based on the NFSA target mandates. However, to instrument the lead, we calculate entitlements based on a counterfactual in which the NFSA was passed in June 2012, one year before it was actually passed.

that were differently affected by NFSA reforms in the same village in the same year. Local economic shocks, such as changes in labor demand, local climate, or macroeconomic shocks to locally prevalent sectors are absorbed by the fixed effects, as are changes to state-level policies. These regressions are akin to a triple-differences approach, in which households whose entitlements were unaffected by NFSA, perhaps because they do not own a PDS ration card, serve as a within-village control group. The estimates, reported in Table (1.9), are very similar to those of our baseline specifications, which suggests that our results are not driven by unobserved time-varying shocks that operate at the state or village level.

One concern about this triple-differences approach is that there may be spillovers between PDS beneficiaries and non-beneficiaries. For example, it is possible that increased access to subsidized PDS grains drives down the price of non-subsidized grain through market competition. This would also benefit households without ration cards, who might therefore also reduce their labor supply. Furthermore, a reduction in labor supply of PDS beneficiaries is likely to lead to an increase in wages of non-beneficiaries who compete in the same labor market. If this is the case, estimates from a triple-difference approach that uses non-beneficiaries as an internal control would be biased downward. To explore this concern, Table (1.10) presents regressions that restrict the sample to PDS beneficiaries (households with either a BPL or an AAY card). The estimates are very similar to those from the whole sample. While the point estimate for labor supply is slightly larger for the beneficiaries-only sample, the wider confidence interval does not allow us to rule out that the effects are the same across samples, suggesting that spillovers are of limited magnitude.

1.5.2 Wage Stability against Productivity Shocks

Wages in poor and underdeveloped regions, respond strongly to fluctuations in agricultural productivity, caused for example by rainfall shocks. Bad rainfall may result in lower crop yield, reducing the demand for labor at harvest time and thereby depressing wages, with severe welfare consequences for the poor. The negative welfare effects of agricultural productivity shocks are particularly strong for the poorest, who rely on wage labor as an income smoothing strategy. Previous studies have shown that the poor increase their market labor supply in response to agricultural shocks, to make up for lost income from agricultural production (Kochar, 1999). This increase in labor supply causes wages to deteriorate, which further increases the poor's need to generate income, leading to a vicious cycle of high labor supply and low wages (Jayachandran, 2006). A safety-net like the PDS could mitigate this vicious cycle by reducing the need to generate income in response to productivity shocks. In this case, we would expect the effect of PDS on labor supply and wages to be particularly large in years with a negative productivity shock.

We test this proposition by considering rainfall as a measure of productivity risk. The ICRISAT villages provide a unique setting to test this proposition, where a majority of households are vulnerable to rainfall shocks (Gine, 2007; Jacoby and Skoufias, 1997; Rosenzweig and Binswanger, 1993). Following (Rosenzweig and Binswanger, 1993), we use the timing of monsoon onset as a rainfall-based productivity shock. This timing is a crucial predictor of agricultural profits, since the early monsoon provides the soil moisture necessary for the initial stages of plant growth. Previous work has shown that agricultural yields and profits are lower in years with a late monsoon onset (Rosenzweig and Binswanger, 1993).

We estimate whether the PDS has greater labor market effects during negative shocks, by considering the interaction between PDS transfer and monsoon onset:

$$Y_{ihst} = \alpha_i + \lambda_t + \delta_s t + \beta_1 R_{vy} + \beta_2 T_{hst} + \beta_3 R_{vy} T_{vst} + \epsilon_{ivt} \tag{1.3}$$

Y_{ihst} is the outcome (labor supply or wages) for individual i in household h, state s, and month t, T_{hst} is the household's PDS transfer value,R_{vy} is the number of days that monsoon onset occurred after June 1 in village v in crop-year y,[19] α_i and λ_t are individual and month fixed effects, and δ_s are state-specific linear time-trends. The PDS transfer value T_{hst} is instrumented with its target value based on the NFSA mandates. Crop-year y is defined

[19] Following (Rosenzweig and Binswanger, 1993), we define the date of monsoon onset as the first day after June 1 with more than 20 mm of rain. In Appendix B, we show that this measure of monsoon onset is highly correlated with alternative rainfall measures. We also validate the use of monsoon onset as a proxy for productivity risk in our sample by showing that it is strongly correlated with village crop yields, production, quantity sold and price.

from September to August, as the effect of monsoon (or harvest season) in India commences from September.[20] The co-efficient on the interaction term β_3 reflects the difference in the effect of PDS expansion between years with more and less favorable rainfall. Standard errors are clustered at the village level.

The results of this estimation, reported in Table (1.11), show that late monsoon increases labor supply and decreases wages, while a more generous PDS transfer reduces labor supply and increases wages. The interaction terms suggest that PDS transfers decrease labor supply and increase wages more strongly in years with negative rainfall shocks. The wage estimates suggest that a 1 rupee increase in PDS transfer when monsoon onset is delayed by 10 days (or at the 25th percentile of monsoon shock) increases wages by 0.199 Rs/day (=0.193 + 0.006), whereas the wage increases by 0.24 Rs/day (=0.193 + 0.05) when monsoon is delayed by 70 days (or at the 95th percentile of monsoon shock). For a PDS program expansion, as in Bihar, the same estimates imply that, a 70 rupees per-adult increase in PDS transfer value increases wages by 14 Rs/day (=0.199*70) when monsoon is delayed by 10 days, whereas the wage increases by 17 Rs/day (=0.24*70) when monsoon is delayed by 70 days. These results suggest that PDS transfers help stabilize labor markets against the vicious cycle of high labor supply and low wages that occurs in years with negative productivity shocks.

We further explore the seasonality of this stabilizing effect by including interactions with seasonal dummies. Results reported in Table 1.12) show that the wage stability effect of PDS is concentrated in the lean season. This is consistent with a mechanism in which poor households use market labor in the lean season to make up for lower incomes during the agricultural season. Since labor demand is lower in the lean season, this would have a particularly large effect on wages. Our results suggest that the effect of PDS transfers on wages is largest during the lean period, when poor households most rely on market labor income.

Overall, our results imply that increases in the generosity of the PDS transfers are effective in moderating the impact of negative economic shocks on labor market outcomes. These results are consistent with the findings in Jayachandran (2006), that productivity shocks cause larger changes to

[20] For instance, monsoon onset in 2013 would correspond to monthly labor supply from September 2013 to August 2014.

labor supply and wages if workers are closer to subsistence level because such workers supply labor less elastically. A safety net like the PDS can relax the subsistence constraint and thus make labor market outcomes less sensitive to production shocks.

1.6 Distributional Impact

The previous analysis suggests that the expansion of PDS transfers after the NFSA reforms led to an increase in wages, which benefits net labor sellers and hurts net labor buyers. Since net labor sellers are likely to be poorer than net labor buyers, this effect is likely to have pro-poor distributional impacts. We estimate the distributional impact of the wage effect in terms of household welfare for different consumption quintiles.

Following Imbert and Papp (2015), we calculate the welfare effect of an equilibrium wage increase from the PDS program in terms of compensating variation or the income needed to compensate households for a policy change

$$\text{Welfare gain}_i = (\text{Net labor earnings})_i * \frac{dW/W}{dT} \tag{1.4}$$

A step-by-step estimation of welfare gains for different consumption quintiles are reported in Table 1.13. The first term on the right-hand side of eq.(3.5) is estimated using the available data in the ICRISAT panel on total labor earnings from the Employment Schedule and total labor payments to hired laborers from the Cultivation Schedule. Estimates of total labor earnings and total labor payments/costs by consumption quintile are reported in Rows (3) and (5) in Table 2.6. Net labor earnings (Row 6) is calculated as the difference between total labor earnings and total labor costs (Row 3 - Row 5). As households in the poorest quintile are net suppliers of labor, the net labor earnings is the highest for the poorest quintile and decreases for higher quintiles. The second term $\frac{dW/W}{dT}$ in equation (3.5), which represents the equilibrium wage change due to a change in PDS transfer value, is substituted as 6.6%, based on the estimated 15 Rupees increase in wages brought about by a 70 Rupees increase in PDS transfer value, as reported in Table 1.6. The resulting net welfare gain from the wage change is 6.6% multiplied by net labor earnings for each quintile.

The direct gains from the PDS program is substituted as the actual PDS transfer value received by the households at current prices (Row 9). As PDS is a targeted program, the poorer quintiles receive larger benefits. Households in the richest quintile also receive a modest amount from the PDS, probably due to inclusion errors in targeting. The extent of inclusion and exclusion errors in ration card allocation has been widely discussed and highlighted (For example, see Dreze and Khera (2010) and Niehaus et al. (2013)). In our data, about 35% of households in the richest quintile hold a BPL ration card. Further, the state of Andhra Pradesh had a quasi-universal PDS, wherein APL households also received the same benefits as BPL.

The total gain is computed as the sum of direct gains from the PDS program and the indirect gains from the wage change (Row 8 + Row 9). Figure 1.5 depicts the numerical estimates of total welfare gains as a fraction of household consumption, Rows 12-14 in Table 1.13. The figure shows that the total gains from the PDS program for the poorest quintile is about 13% of household consumption. The indirect gains through the wage channel are highest for households in the poorest quintile, since these are the largest sellers of labor. This indirect effect from the wage change increases the welfare benefit for the poorest quintile by an additional 30% (Row 11). In contrast, for households in the richest quintile who are net labor buyers, the increase in labor costs result in a welfare loss. However, the welfare loss from the program for the richest quintile, expressed as a fraction of total expenditure, is only around 1 percent of total expenditures (Row 9).

Furthermore, the analysis in Section 6 suggests the equilibrium wage increase due to an expansions in the PDS program is greater in years with a negative monsoon shock. In order to measure the distribution of welfare gains for different intensities of rainfall shocks, we simulate the effect of PDS transfer value on equilibrium wages for different values of monsoon onset, based on the coefficient estimates in Table 1.13. These predicted marginal effects and the corresponding welfare gains at the 25th and 95th percentile of rainfall shock are reported in Rows 15 and Row 17. The numerical estimates, also depicted in a bar graph in Figure 1.6, shows that the welfare gains from the wage increase is not only highest for the poorest quintile, also the gains are larger when households face a negative monsoon shock of greater magnitude.

In summary, the distributional impact analysis suggests that the equilibrium effects of the PDS program on the labor market are significantly welfare improving for poor households, especially the poorest quintile. These results are highly relevant for policy as they imply that the labor market effects further strengthen the pro-poor targeted objective of the PDS program. In addition, as these general equilibrium effects are stronger when households face adverse productivity shocks, our results suggest that the PDS program can play an important role in preventing the vicious cycle of high labor supply and low wages that afflicts poor households in bad years. Our results also highlight the importance of accounting for local general equilibrium effects (Acemoglu, 2010). Ignoring these labor market effects would lead us to underestimate the impact of PDS program on the welfare of the poor.

1.7 Conclusion

In this study, we estimate the effect of India's food subsidy program, the PDS, on labor supply and wages. Using state-level changes in the program that occurred after the National Food security Act of 2013, we show that increases in the generosity of the in-kind food subsidy led to lower labor supply and higher wages. The disaggregated results suggest that the effect of PDS was larger for the casual unskilled labor market, which in principle is the desired population that PDS is targeted towards. Further, we find that the effect was particularly strong in years with late monsoon onset, a rainfall shock associated with reduced agricultural productivity. This buffer effect was greater for women in farm labor. Our results suggest that in-kind food subsidies can thus improve the welfare of the poor through a labor market effect in addition to their direct effect on food consumption and nutrition. Our results highlight the importance of accounting for local general equilibrium effects; ignoring these effects would lead us to underestimate the impact of PDS on the welfare of the poor.

1.8 Figures and Tables

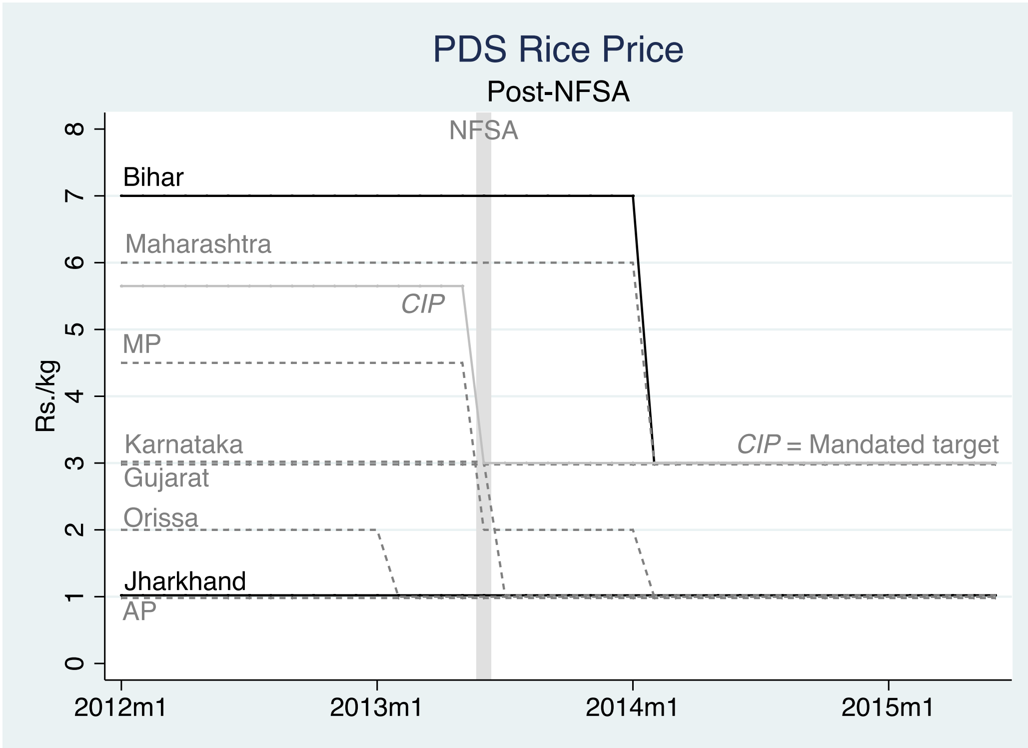


Figure 1.1: PDS Rice price for BPL households pre and post-NFSA

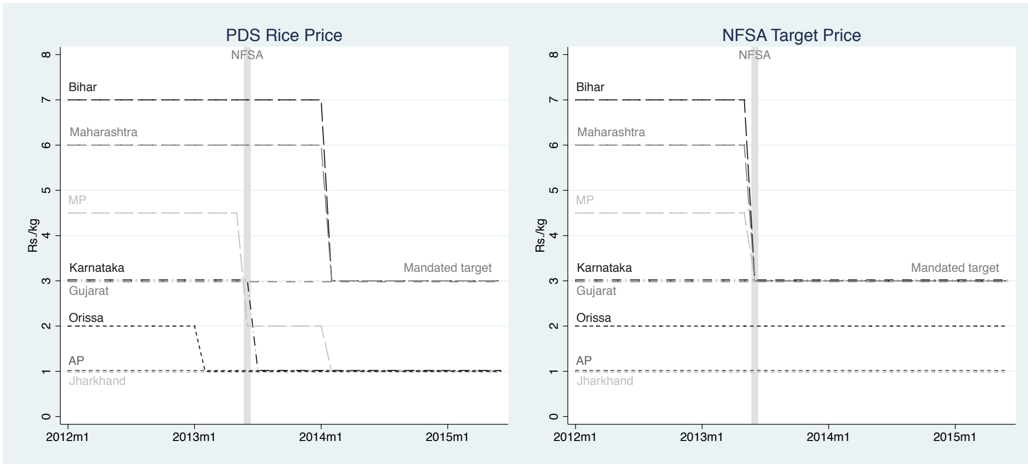


Figure 1.2: Actual PDS rice price vs NFSA rice price (instrument) for BPL households, pre and post-NFSA

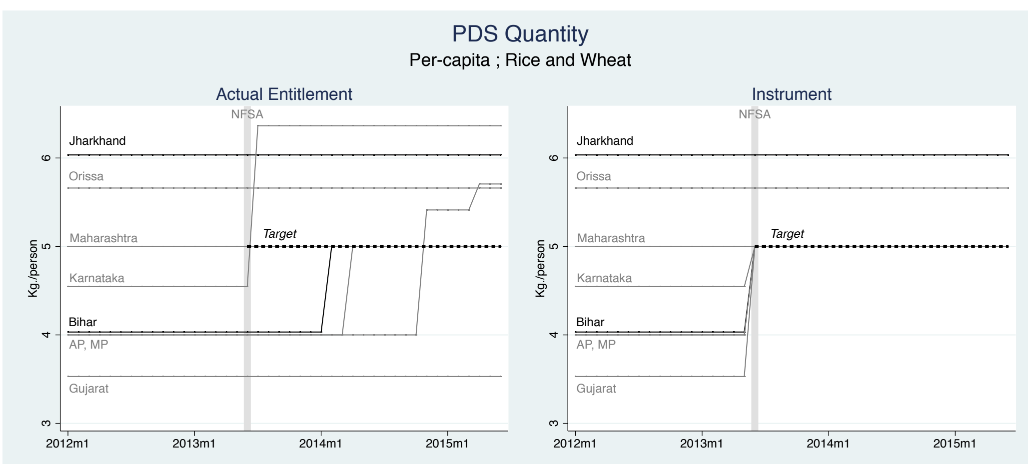


Figure 1.3: Actual PDS quantity vs NFSA target quantity (instrument) for BPL households pre and post-NFSA

Figure 1.4: Actual PDS subsidy value and NFSA value for BPL households pre and post-NFSA

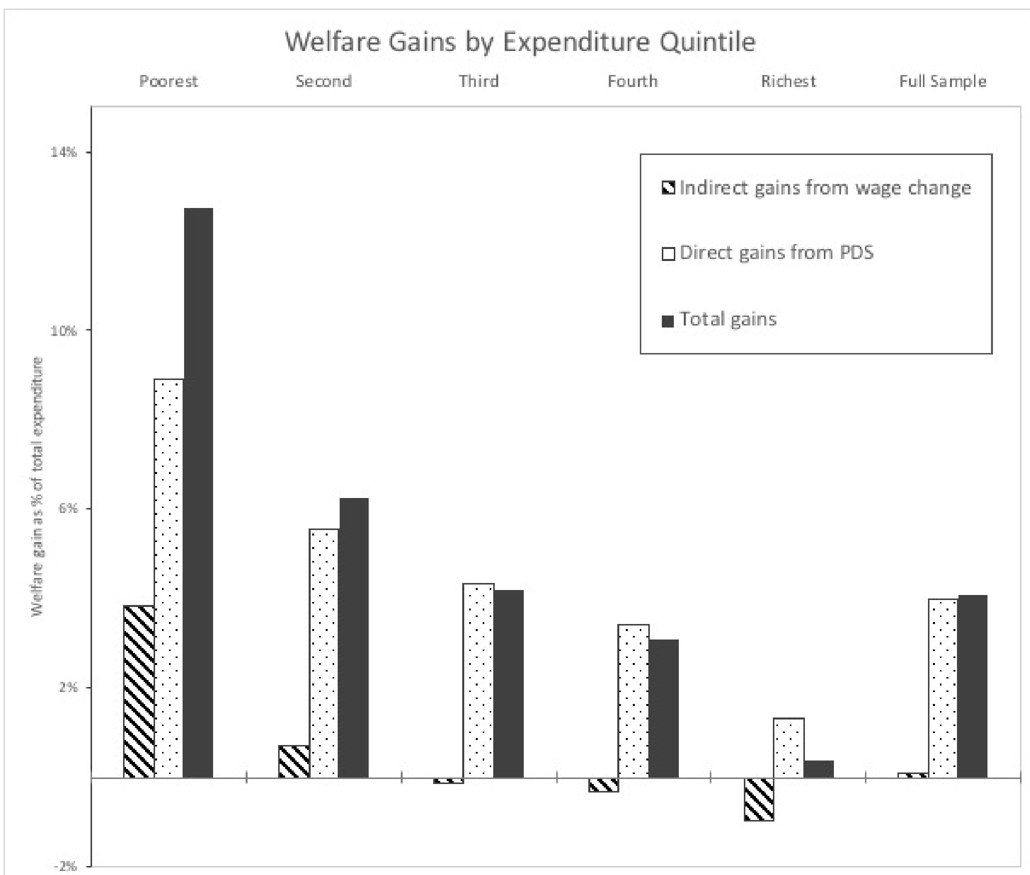


Figure 1.5: Indirect and Direct welfare gains as a fraction of total expenditures

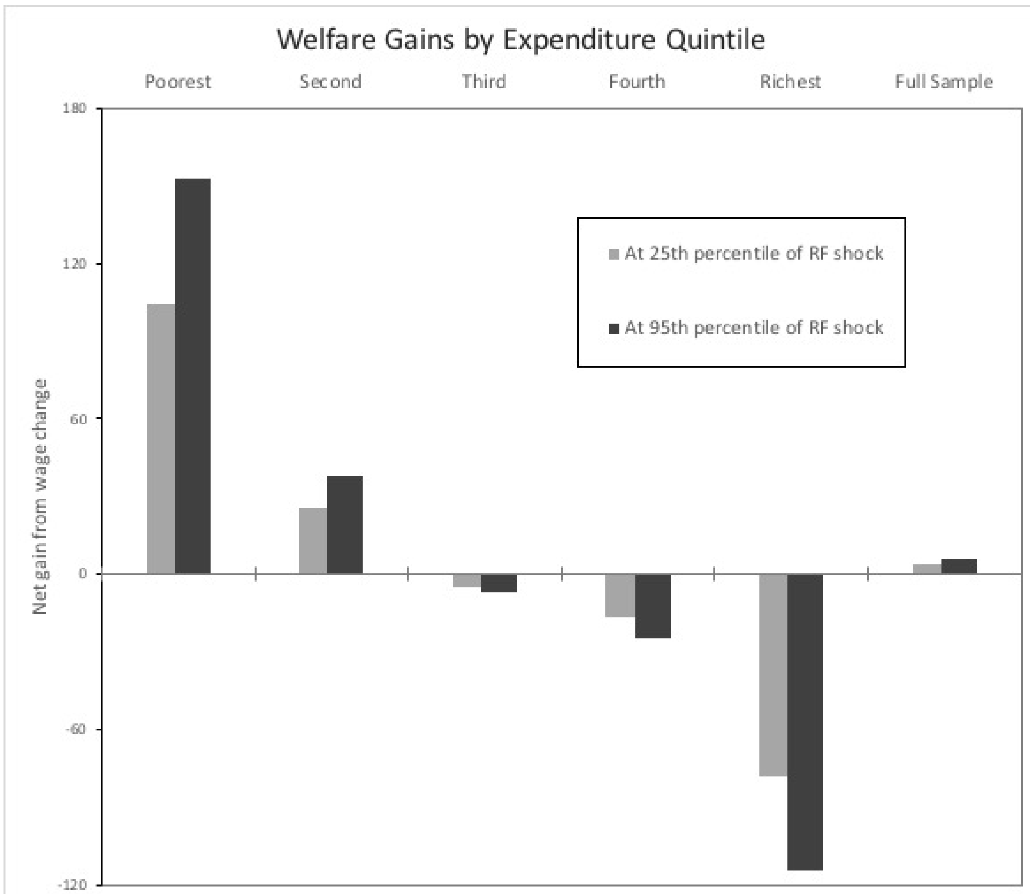


Figure 1.6: Gains from wage change and monsoon shock

Table 1.1: State-level PDS entitlements, pre and post NFSA

	Item	(A) PRE-NFSA Quantity	(A) PRE-NFSA Price	(B) POST-NFSA Quantity	(B) POST-NFSA Price	(C) NFSA Target (IV) Quantity	(C) NFSA Target (IV) Price
				Oct-14			
Andhra Pradesh†	Rice	4 kg/indv (Max of 20kg/HH)	1 Re/kg	6 kg/indv (No ceiling)	1 Rs/kg	5 kg/indv	1 Rs/kg
	Wheat	No wheat ration					
				NFSA - Feb-14			
Bihar	Rice	15 kg/hh	7 Rs/kg	3kg/indv	3 Rs/kg	3kg/indv	3 Rs/kg
	Wheat	10 kg/hh	5 Rs/kg	2kg/indv	2 Rs/kg	2kg/indv	2 Rs/kg
Gujarat‡	Rice	5 kg/hh	3 Rs/kg	No changes		1kg/indv	3 Rs/kg
	Wheat	13 kg/hh	2 Rs/kg			4kg/indv	2 Rs/kg
Jharkhand	Rice	35 kg/hh	1 Re/kg	No changes		No changes	
	Wheat	No wheat ration					
				Anna Bhagya Yojana Jul-13			
Karnataka††	Rice	4 kg/indv	3 Rs/kg	30 kg/hh	1 Rs/kg	4kg/indv	3 Rs/kg
	Wheat	1 kg/indv (Max 25kg/HH)	3 Rs/kg	3 kg/hh	3 Rs/kg	1kg/indv	2 Rs/kg
				NFSA - Feb-14			
Maharashtra	Rice	10 kg/hh	6 Rs/kg	2kg/indv	3 Rs/kg	2kg/indv	3 Rs/kg
	Wheat	15 kg/hh	5 Rs/kg	3kg/indv	2 Rs/kg	3kg/indv	2 Rs/kg
				NFSA Apr 2014			
Madha Pradesh‡‡	Rice	2 kg/hh	4.5 Rs/kg	1kg/indv	1 Rs/kg	1kg/indv	3 Rs/kg
	Wheat	18 kg/hh	3 Rs/kg	4kg/indv	1 Rs/kg	4kg/indv	2 Rs/kg
				Feb-13			
Orissa	Rice	25 kg/hh	2 Rs/kg	25kg/hh	1 Rs/kg	No changes	
	Wheat	No wheat ration					

∗ NFSA Targets assume that all states complied with the mandate in June 2013, when NFSA was officially enacted.

†Andhra Pradesh decreased Rice price to Re. 1/kg in Nov-11. AP split into two states in 2014, namely Telangana and AP. In Oct 2014, Telangana increased rice quantity entitlement to 6kg/member and in April 2015 AP increased the quantity entitlement to 5kg/member.

‡ Gujarat enacted NFSA in 2016, which is not captured in our study time frame

†† Karnataka reduced wheat price to Re 1/kg in Oct-13 under the Anna Bhagya Yojana

‡‡ Madhya Pradesh introduced Mukhyamantri Annapurna Scheme in July 2013 and reduced Rice price to 2 Rs/kg and wheat price to Re 1/kg. In Feb 2014, MP further reduced Rice price to Re 1/kg.

Table 1.2: Summary Stats

	AAY	BPL	APL/NoCard	Total
Number of HHs	105	579	533	1217
Number of members in the HH	4.706	4.724	5.040	4.861
	(2.125)	(2.238)	(2.377)	(2.296)
Nutrient and Calorie intake				
Calorie intake (Kcals)	2115.7	2032.5	2009.1	2029.7
	(740.9)	(794.8)	(746.3)	(770.1)
Protein intake (gms)	56.61	52.06	54.04	53.31
	(22.43)	(21.92)	(21.18)	(21.69)
Fat intake (gms)	39.21	37.92	46.74	41.84
	(19.53)	(35.99)	(25.96)	(31.07)
Consumption Quantity (in Kgs)				
Total Staple Cereals	12.82	11.46	10.43	11.13
	(5.886)	(5.546)	(5.608)	(5.648)
Quantity of pds grain consumed	7.259	5.400	1.183	3.742
	(3.905)	(3.883)	(2.511)	(4.067)
Pulses	1.066	1.035	0.964	1.007
	(0.704)	(0.811)	(0.677)	(0.748)
Expenditure and Income (in 2010 value)				
Food expenditure	558.2	596.7	715.6	644.7
	(236.4)	(305.3)	(359.1)	(330.6)
Non-food expenditure	518.7	667.3	757.5	693.4
	(1708.2)	(3221.9)	(3394.4)	(3197.9)
Total expenditure	1077.3	1264.7	1475.6	1339.4
	(1760.8)	(3278.9)	(3477.1)	(3267.4)
Implict PDS Subsidy	198.9	127.1	10.54	83.05
	(131.2)	(69.42)	(22.64)	(91.77)
Income total	1567.4	2243.5	2680.4	2375.9
	(4128.6)	(16946.8)	(13784.3)	(14878.5)

Standard deviation in parentheses. All values, except number of HHs and household size, represent the adult equivalent per household. Nutrient and Calorie intake is measured daily per-adult equivalent. Consumption quantity, expenditure and income is measured monthly per-adult equivalent.

Table 1.3: Validation of NFSA implementation

Panel A: Effect of NFSA Target on Entitlement			
	Entitlement		
	Quantity (kg)	Price (Rs/kg)	Transfer value (in 2010 Rs)
NFSA Target	0.870***	0.694***	0.781***
	(0.017)	(0.010)	(0.047)
F-stat			270.59
Observations	68622	70410	69148

Panel B : Effect of Entitlement on Consumption			
	Actual consumption		
	Quantity (kg)	Price (Rs/kg)	Transfer value (in 2010 Rs)
PDS entitlement	0.531***	0.704***	0.550***
	(0.042)	(0.040)	(0.041)
Observations	68622	70410	69148

Panel C : Effect of NFSA Target on Consumption			
	Actual consumption		
	Quantity (kg)	Price (Rs/kg)	Transfer value (in 2010 Rs)
NFSA Target	0.402***	0.484***	0.353***
	(0.042)	(0.042)	(0.073)
Observations	68622	70410	69148

Standard errors clustered at the village level in paranthesis. * $p<0.10$ ** $p<0.05$ *** $p<0.01$. Each coefficient estimate is from a separate regression with column heading as outcome variable and row heading as the regressor variable. Each regression is estimtated with household and time fixed effects. PDS entitlement refers to actual household level entitlements calculated based on the current year's state-level PDS policies baseline household size and ration card status, as described in Section 4. NFSA target value refers to the counterfactual entitlements assuming that all states expanded PDS entitlements just enough to comply with the NFSA mandates, as described in Section 2.2

Table 1.4: Effect of PDS transfer on Market Labor Supply

	Market Labor Supply (Mean = 18.92 days/month)			
PDS Subsidy value	-0.00733**	-0.00768**	-0.00839***	-0.00810*
(IV NFSA value)	(0.00306)	(0.00276)	(0.00252)	(0.00360)
Individual FE	X	X	X	X
Month FE	X	X	X	X
State trends	X			
Village trends		X	X	X
State-seasonal month FE			X	X
SE clustered at State-level				X
F-stat on excluded instrument	30.6	22.3	16.9	8.3
Observations	292215	292215	292215	292215

* p<0.10 ** p<0.05 *** p<0.01.

Table 1.5: Effect of PDS Transfer on Market Wages

	Market Wages (Mean = 227 Rs/day)			
PDS Subsidy value	0.21897***	0.16314**	0.17011***	0.16350**
(IV NFSA value)	(0.07638)	(0.05025)	(0.04801)	(0.04754)
Individual FE	X	X	X	X
Month FE	X	X	X	X
State trends	X			
Village trends		X	X	X
State-seasonal month FE			X	X
SE clustered at State-level				X
F-stat on excluded instrument	30.6	22.3	16.9	8.3
Observations	104040	104040	104040	104040

* p<0.10 ** p<0.05 *** p<0.01.

Table 1.6: Effect of PDS Subsidy on labor market

	Market Labor Supply			Wages		
	Total market labor	Non-farm labor	Farm labor	Market wage	Non-farm wage	Farm wage
OLS						
PDS Subsidy value	-0.00062	-0.00138	0.00077	0.02231	0.04193	0.00414
	(0.00110)	(0.00096)	(0.00048)	(0.03359)	(0.04211)	(0.01294)
IV (Instrument: NFSA value)						
NFSA value	-0.00768**	-0.00630*	-0.00150	0.16314**	0.18185**	0.09002***
	(0.00276)	(0.00269)	(0.00104)	(0.05025)	(0.06665)	(0.02561)
Individual FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Village Trend	X	X	X	X	X	X
F-stat on excluded instrument	12.845	12.847	12.868	45.569	47.257	11.225
Mean	18.92	14.03	4.39	226.93	269.3	150.5
Observations	292215	292536	290818	104040	69780	37330

The table reports the effect of PDS subsidy on labor market outcomes - labor supply and wages, for the full sample of individuals. Unit of observation is individual-month. Each column is a separate regression with PDS subsidy value as the regressor variable with individual and month fixed effects and village trends. Column headings describe the outcome variables. Standard errors in paranthesis are clustered at the village level. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table 1.7: Robustness tests for parallel trends in labor supply

	Market Labor Supply (Mean = 18.92 days/month)					
Reduced-form with Instrument						
NFSA target value	-0.00168**	-0.00185**	-0.00184***	-0.00194***	-0.00171***	-0.00191**
	(0.00065)	(0.00073)	(0.00064)	(0.00065)	(0.00057)	(0.00082)
Lead of NFSA target value		-0.00066	-0.00054	-0.00040	-0.00041	-0.00043
		(0.00061)	(0.00055)	(0.00054)	(0.00067)	(0.00048)
Individual FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Village trends	X	X	X	X	X	X
State-seasonal month FE			X			
State-month FE				X		X
Village-month FE					X	
Year FE # Baseline HH characterics						X
Observations	293308	23552	23552	23552	23552	232043

* $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table 1.8: Robustness tests for parallel trends in wages

	Market Wages (Mean = 227 Rs/day)				
Reduced-form with Instrument					
NFSA target value	0.05149**	0.03946*	0.04177**	0.04170**	0.03389**
	(0.02484)	(0.01992)	(0.01586)	(0.01570)	(0.01605)
Lead of NFSA target value		-0.00924	-0.01247	-0.01176	-0.02319
		(0.02554)	(0.02633)	(0.02664)	(0.02825)
Individual FE	X	X	X	X	X
Month FE	X	X	X	X	X
Village trends	X	X	X	X	X
State-seasonal month FE			X		
State-month FE				X	X
Year FE # Baseline HH characterics					X
Observations	104040	83765	83765	83765	83587

* p<0.10 ** p<0.05 *** p<0.01.

Table 1.9: Robustness to state-time fixed effects

	Market Labor Supply (Mean = 18.92 days/month)				Market Wages (Mean = 227 Rs/day)		
PDS Subsidy value	-0.00768**	-0.00839***	-0.00840***	-0.00810***	0.16314**	0.17011***	0.17108***
(IV NFSA value)	(0.00276)	(0.00252)	(0.00250)	(0.00251)	(0.05025)	(0.04801)	(0.04901)
Individual FE	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X
Village trends	X	X	X	X	X	X	X
State-seasonal month FE		X				X	
State-month FE			X				X
Village-month FE				X			
F-stat on excluded instrument	22.3	16.9	16.9	16.9	22.3	16.9	16.9
Observations	292215	292215	292215	292215	104040	104040	104040

* p<0.10 ** p<0.05 *** p<0.01.

Table 1.10: Robustness to spillovers

	Market Labor Supply			Wages		
	Full sample	Age 18-65	PDS Benefeciaires	Full sample	Age 18-65	PDS Benefeciaires
IV (Instrument: NFSA value)						
PDS Subsidy Value	-0.00768**	-0.00730**	-0.01155*	0.16314**	0.19669***	0.16833*
	(0.00276)	(0.00273)	(0.00513)	(0.05025)	(0.05239)	(0.07299)
Individual FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Village Trend	X	X	X	X	X	X
Observations	292215	216625	183853	104040	96761	77053

* p<0.10 ** p<0.05 *** p<0.01.

Table 1.11: Labor market effects with monsoon shock interaction

	Panel A : Total market		Panel B : Non-farm		Panel C : Farm	
	Labor supply	Wages	Labor supply	Wages	Labor supply	Wages
PDS transfer	-0.00555*	0.19333**	-0.00448*	0.24100**	-0.00105	0.09525*
(IV - NFSA value)	(0.00321)	(0.08101)	(0.00232)	(0.10633)	(0.00196)	(0.04972)
Monsoon shock	0.01124	-0.34060*	0.00566	-0.37871*	0.00534	-0.21962
	(0.00681)	(0.19157)	(0.00448)	(0.20147)	(0.00367)	(0.17492)
Interaction	-0.00003**	0.00066**	-0.00002	0.00058*	-0.00001**	0.00052
	(0.00001)	(0.00032)	(0.00001)	(0.00033)	(0.00001)	(0.00035)
Individual FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
State Trend	X	X	X	X	X	X
Observations	292215	104040	292536	69780	290818	37330

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. The table reports the effect of PDS transfers on the labor market, interacted with monsoon shock. Unit of observation is individual-month.The results are for the full sample of individuals. Each column is a separate regression with PDS transfer value (instrumented with NFSA target value), monsoon onset and thier interaction as the regressor variables with individual and year fixed effects and state trends. Column headings describe the outcome variables.

Table 1.12: Seasonality in labor market effects

	Total market labor			Market wage		
IV (Instrument: NFSA target value)						
NFSA value x Lean	-0.00746**	-0.00736**	-0.00695**	0.22454***	0.22123***	0.20026**
	(0.00313)	(0.00317)	(0.00299)	(0.07678)	(0.07630)	(0.07385)
NFSA value x Peak	-0.00722**	-0.00714**	-0.00702**	0.21542***	0.21339***	0.20588***
	(0.00302)	(0.00308)	(0.00314)	(0.07577)	(0.07592)	(0.07394)
Rainfall						
Monsoon onset x Lean		0.00277	0.00861		-0.10166	-0.39159**
		(0.00493)	(0.00680)		(0.10602)	(0.17889)
Monsoon onset x Peak		0.00393	0.00655		-0.18565	-0.26689
		(0.00429)	(0.00386)		(0.11862)	(0.16580)
Buffer effect						
Interaction x Lean			-0.00002			**0.00079****
			(0.00001)			**(0.00032)**
Interaction x Peak			-0.00001			**0.00026**
			(0.00001)			**(0.00026)**
Individual FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
State Trend	X	X	X	X	X	X
Mean	18.92	18.92	18.92	226.93	226.93	226.93
Observations	292215	292215	292215	104040	104040	104040

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. The table reports the effect of PDS transfers on the labor market, interacted with monsoon shock. Unit of observation is individual-month.The results are for the full sample of individuals. Each column is a separate regression with PDS transfer value (instrumented with NFSA target value), monsoon onset and their interaction as the regressor variables with individual and year fixed effects and state trends. Column headings describe the outcome variables. Dry is a dummy variable equal to one for January to June. Rainy is a dummy variable for July to Dec.

Table 1.13: Welfare Gains by expenditure quintile

		Expenditure quintile					Full sample	Remarks
		Poorest	Second	Third	Fourth	Richest		
	Household expenditures and income							
1)	Monthly HH consumption per capita	657	953	1205	1556	2139	1491	Sum stat
2)	Total monthly consumption	3071	4210	4812	5734	9241	5418	Sum stat
3)	Total earnings permonth for adults doing casual labor	2063	786	417	371	196	766	Sum stat
4)	Casual earning as a fraction of household consumption	0.67	0.19	0.09	0.06	0.02	0.14	(3) / (2)
	Gains in household welfare from wage increase							
5)	Estimated monthly labor costs per household	198	322	503	675	1594	694	Cultivation Schedule
6)	Net labor earnings per month	1865	464	-86	-304	-1398	72	(3) - (5)
7)	Wage change	6.3%	6.3%	6.3%	6.3%	6.3%	6.3%	Estimated from average effects
8)	Net income gain from wage change	117.5	29.2	-5.4	-19.2	-88.1	4.5	(6) * (7)
	Direct Gains from PDS transfer							
9)	Actual monthly PDS transfer valure received at current prices per household	274	234	208	196	123	216	Sum stat
	Total gains							
10)	Total gain from PDS transfer and wage change	391.1	263.5	202.6	176.8	34.9	220.3	(9) + (8)
	Welfare gains from wage change							
11)	As a fraction of total gains	30%	11%	-	-	-	2%	(8) / (10)
	Welfare gains as a fraction of total expenditure							
12)	Indirect gains from wage change	3.8%	0.7%	-0.1%	-0.3%	-1.0%	0.1%	(8) / (2)
13)	Direct gains from PDS transfer	8.9%	5.6%	4.3%	3.4%	1.3%	4.0%	(9) / (2)
14)	Total gain as a fraction of total expenditures	12.7%	6.3%	4.2%	3.1%	0.4%	4.1%	(10) / (2)
	Welfare gains and monsoon shock							
15)	Wage increase at 25th percentile of monsoon shock	5.6%	5.6%	5.6%	5.6%	5.6%	5.6%	Estimated from buffer effects
16)	Net income gain from wage change at 25th percentile	104.4	26.0	-4.8	-17.0	-78.3	4.0	(10) * (6)
17)	Wage increase at 95th percentile of monsoon shock	8.2%	8.2%	8.2%	8.2%	8.2%	8.2%	Estimated from buffer effects
18)	Net income gain from wage change at 95th percentile	152.9	38.0	-7.1	-24.9	-114.6	5.9	(12) * (6)
19)	Total gains at 25th percentile of monsoon shock	378.0	260.3	203.2	178.9	44.7	219.8	(11) + (10)
20)	Total gains at 95th percentile of monsoon shock	426.5	272.3	200.9	171.0	8.4	221.7	(13) + (10)

Notes:

CHAPTER 2

DO STAPLE FOOD SUBSIDIES IMPROVE NUTRITION?

2.1 Introduction

Food subsidies are a widely used tool for improving the food security of the poor. About 1.5 billion people worldwide receive in-kind food subsidies (Alderman et al., 2018), which provide a rationed quantity of subsidized food, typically consisting of staples such as rice, wheat or bread. For example, the Raskin program in Indonesia provides rice to 62 million people, the Public Distribution System (PDS) in India provides rice and wheat to 800 million people and Tamween program in Egypt provides Baladi bread and wheat flour to 82 million people. While emerging-market governments increasingly debate moving from in-kind subsidies to cash transfers (Blattman et al., 2017), in-kind transfers still remain the predominant form of assistance in low and middle income countries. For example, in-kind programs in India and Egypt are the largest form of social assistance in both countries, accounting for 53% and 60% of their social assistance budget (Alderman et al., 2018).

Among the many justifications for in-kind food subsidies, perhaps the most cited is improved nutrition.[1] Proponents argue that providing subsidized staple food will increase consumption of the staple while decreasing expenditure, thereby allowing recipients to spend more of their budgets on nutritious higher value foods. However, opponents contend that subsidizing staple food primarily encourages staple cereal consumption, and thus may crowd-out more nutritious food items and potentially reduce dietary diversity.

Theoretically, the effect of an in-kind staple food subsidy on overall food consumption depends on a number of factors, including whether the subsidy is infra-marginal or extra-marginal[2], whether food is a normal or inferior

[1] See Currie and Gahvari (2008) for a review on the justifications for in-kind transfers

[2] An in-kind subsidy is considered to be infra-marginal if the quantity of subsidized food is smaller than the quantity the household would have consumed without the subsidy, and

good, and whether the household is subject to liquidity constraints or intra-household bargaining dynamics. In the simplest case of an infra-marginal subsidy in a unitary household without liquidity constraints, the subsidy has a pure income effect and may increase or decrease staple food consumption, depending on whether food is a normal or inferior good. In the case of an extra-marginal subsidy, the effect on consumption would also depend on the magnitude of the price elasticity of food. Previous research has shown that staple foods can exhibit Giffen behavior, so that food subsidies may decrease consumption (Jensen and Miller, 2011).

In this paper, we examine the impact of India's food subsidy program - the PDS - on food consumption and nutrition. The PDS is the world's largest in-kind food subsidy program, and is targeted towards the poor, with a primary objective to provide food security. The PDS supplies a ration of staple food (mainly rice and wheat) at highly subsidized prices through a network of retail outlets known as fair price shops. With more than 530,000 fair price shops, that cover around 85% of the villages in the country, the PDS is the most far reaching social safety net in India. The Indian government's spending on food subsidies (US $18.9 billion in 2015) is about three times the size of NREGA - the next-largest social assistance program (Government of India, 2017). The efficacy of such a massive program in addressing the persistent problem of malnutrition in India holds important lessons for future food security and social welfare policy both in India and in many other developing countries with similar programs.

To estimate the effect of food subsidies, we exploit state-level changes in PDS subsidies that resulted from the National Food Security Act (NFSA) of 2013. As one of its central provisions, the NFSA mandated generous national targets for quantities and prices at which state governments had to provide PDS rations. For instance, the minimum monthly PDS entitlements for the poor were expanded from varying state levels to 2kg at 3 Rs/kg for rice and 3 kg at 2 Rs/kg for wheat. To comply with these new national targets, states whose PDS programs were less generous before the NFSA were forced to expand subsidies more than states who were already in compliance.[3] The

extra-marginal if the subsidized quantity is larger.

[3]For instance, the state of Bihar reduced its prices for PDS rice from 7 to 3 Rs/kg. In Jharkhand, where the price of PDS rice was already below the new target at 1 Rs/kg, the price remained unchanged.

resulting policy variation lends itself well to estimating the causal effect of food subsidies since it came from a national rule and was therefore unlikely to be correlated with changes in local policies or economic conditions.

We combine the policy variation generated by the NFSA with household-level data on food consumption from ICRISAT's "Village Dynamics in South Asia" panel between 2010 and 2015. Crucially, for our study, the ICRISAT data contains information on the type of PDS ration card a household possesses. We combine this information with data on state level PDS policies to generate a precise measure of the value of the PDS subsidy a household is entitled to receive at every point in time.[4] These data allows us to estimate the effect of the PDS subsidy on household consumption in a difference-in-differences type regression that controls for household, state and time fixed effects. Our results are robust to including household-specific time-trends, and to a triple-difference approach that controls for a state-by-month fixed effects.

We find that increases in the PDS subsidy substantially improve nutrition. In addition to increasing consumption of staple cereals, PDS subsidies "crowd-in" consumption of diverse food types including pulses, milk and milk products, oils, sugar, fruits and vegetables. Consequently, the PDS subsidy increases overall calorie, protein and fat intake. A 100 rupee (monthly) increase in subsidy, equivalent to the PDS increase in the state of Karnataka in 2013, translates to an increased daily intake of 449kcal in intake, 10.9 grams increase in protein and 8.5 grams in fat intake per-adult. These nutritional improvements correspond to around 17% increase in energy and protein intake, 10% increase in fat intake and are large relative to those found by previous studies of the PDS system and other kinds of food subsidies (Kochar, 2005; Kaushal and Muchomba, 2015; Tarozzi, 2005; Kaul, 2018; Jensen and Miller, 2011). We find that PDS beneficiaries consume 83% of the subsidy value in the form of food,[5] suggesting that the transfer does not cause them to substitute away from non-subsidized food.

We further explore mechanisms that may explain these large effects of food

[4] Information on the PDS policy changes comes from personal fieldwork and government records, which we combine to document 11 policy changes to the price and quantity of rice and wheat that beneficiary households are mandated to receive from the PDS.

[5] We follow the literature in calculating the implicit value of the PDS subsidy as the product of the subsidized quantity and the price discount (difference between the average market and specific PDS price)

subsidies on nutrition. Several researchers have proposed intra-household bargaining as an important factor in determining how food subsidies translate to food consumption (Senauer and Young, 1986; Orazem, 1999; Breunig and Dasgupta, 2005). For example, in some societies women have more control over the food budget whereas men control non-food expenditures (Armand et al., 2016; Angelucci and Attanasio, 2009; Attanasio et al., 2011; Schady and Rosero, 2008), so that resources are not treated as completely fungible across the two budget domains. In this scenario, an in-kind subsidy may increase the effective budget share controlled by women and have a larger effect on food consumption, as compared to non-food consumption (Breunig and Dasgupta, 2005).[6]

To this end, we use the ICRISAT's panel data on the role of gender in household decisions to generate proxies for bargaining power over the food budget. Our results suggest that households where women have more control over the food budget spend a significantly larger fractions of the implicit PDS transfer on food and a smaller fraction on temptation goods such as alcohol and cigarettes. These results are consistent with a model in which some households have atleast partially separate food and non-food budgets. As a result, households in which women control the food budget spend the PDS transfer predominantly in the form of food and other items preferred by women.

This study adds important new evidence to the literature on nutritional effects of food subsidies. The previous evidence on this topic is mixed, with many studies that find small or even negative effects of food subsidies on food consumption (e.g. Kochar (2005), Jensen and Miller (2011), Kaushal and Muchomba (2015)). Kochar (2005) and Kaushal and Muchomba (2015) estimated the effect of nationwide increases in the generosity of PDS subsidies on food consumption of poor households, using non-poor households as a control group. Kochar (2005) found that an initial increase in generosity of the PDS subsidy in the late 1990s only led to a marginal increase in the caloric intake of the poor. Similarly, Kaushal and Muchomba (2015) found that a later increase in PDS subsidies in 2002 had no effect on nutritional

[6] Another justification of in-kind food transfers, in the context of intra-household allocation, is that food is spent equitably within the household, while cash can be cornered by certain individuals (Dreze, 2011). Although a few studies find that food is distributed equally within the household (Pitt et al., 1990; Senauer et al., 1988), the empirical evidence on whether cash may be unequally distributed within the household is scarce.

status. Kaul (2018) used variation in district-level market prices of non-subsidized food to estimate the effect of PDS subsidies and found that they had a small but statistically significant positive effect on food consumption. Tarozzi (2005) studied the effect of an increase in the price of PDS food in a single state, Andhra Pradesh, and found that it had no effect on child anthropometric measures.[7]

Outside of India, the literature on food subsidies and nutrition is more mixed. Results from a randomized control trial in Mexico showed that in-kind food transfers increased nutritional outcomes of poor households in Mexico, but not more so than a cash transfer of equal value (Cunha, 2014; Skoufias et al., 2013; Leroy et al., 2010).[8] Also using a randomized control trial in China, Jensen and Miller (2011) found that rice subsidies had either no effect or a negative effect on nutrition.

There are several reasons why our estimates of nutritional effects of PDS subsidies are larger than those of previous studies. First, we base our analysis on plausibly exogenous state-level changes to the generosity of the PDS subsidy. Previous studies considered either nationwide changes to PDS subsidies (Kochar, 2005; Kaushal and Muchomba, 2015), changes from a single state (Tarozzi, 2005), or variation in non-PDS prices (Kaul, 2018). Our empirical approach allows us to control for a wide range of unobserved variables and address concerns about the endogeneity of non-PDS prices to changes in the PDS subsidy. In addition, the combination of detailed state-level information on PDS policies with household-level data on ration-card status allows us to generate a more accurate measure of PDS entitlement at the household level. Most previous studies of the PDS have relied on repeated rounds of cross-

[7]A different literature examines universalization or reforms of the PDS program (Krishnamurthy et al., 2017; Rahman, 2016; Kishore and Chakrabarti, 2015). For instance, Krishnamurthy et al. (2017) examine the effect of a bundle of policy interventions in Chattisgarh, related to improving the effectiveness of the PDS program, such as technological interventions to improve the grievance redressal system, reducing leakages by increasing the commission for ration shop owners, verification of bogus ration cards and improving supply chain efficiency by increasing the number of ration shops and the amount of rice procured from in-state farmers for PDS distribution. Similarly Kishore and Chakrabarti (2015) examine a bundle of PDS reforms in five states including universalization and several administrative reforms to improve the effectiveness of PDS. In contrast, we examine the effect of a specific policy change - expansion in PDS entitlements.

[8]The program examined by these studies, Mexico's *Programa de Apoyo Alimentario* or PAL, differs from the PDS in that its food transfer component was conditional on attending monthly classes in health, hygiene and nutrition. This makes it difficult to compare the program's effect to that of the PDS and other unconditional in-kind subsidies.

sectional data from the National Sample Survey Organization (NSSO), which does not contain consistent information on whether a household is entitled to PDS subsidies. This makes it difficult to precisely measure household-level access to food subsidies, and may lead to attenuation bias.

Our results offer important implications for the Indian policy debate around the effectiveness of the PDS program. The PDS has been criticized on the grounds that the program is poorly targeted, does not reach the intended beneficiaries and hence may have little impact on nutrition. Furthermore, critics contend that PDS encourages only "empty" staple cereal consumption, and thus may crowd-out more nutritious food items and not improve dietary diversity (Desai and Vanneman, 2015; Gulati et al., 2012). Our results suggest that these criticisms do not hold.

Lastly, our study sheds light on the debate concerning the replacement of PDS with cash transfers in India (Svedberg, 2012; Kotwal et al., 2011; Khera, 2014; Saini et al., 2017; Narayanan, 2011; Gentilini, 2017) and the larger discussion on replacing in-kind subsidies with cash transfers (Gentilini, 2016; Blattman et al., 2017). Our results show that the NFSA and state-level PDS initiatives effectively reached the intended beneficiaries and lead to large improvements in household nutrition. In light of the broader skepticism of in-kind form of assistance, our results imply that in-kind food subsidies are an effective tool in addressing nutrition.

2.2 Public Distribution System of India

The Indian PDS is the world's largest in-kind food subsidy program that supplies food ration to more than 800 million people. With more than 532,000 fair price shops spread across the country, the PDS supply chain operates at a massive scale, covering 85% of villages in India, rendering PDS as the most far reaching of all social safety nets in the country.[9] It is the largest social assistance program in India that accounts for almost 1% of the GDP (approx. 10 billion $US in 2016 (Government of India, 2017)).

The PDS has been in existence prior to India's independence. It was ini-

[9]In 2011, there were 506,198 PDS ration shops (Government of India, 2011b) in 597,608 inhabited villages (Government of India, 2011a). This suggests that as many as 85% of Indian villages were covered under the PDS. The coverage has since increased. In 2016, there were 532,000 FPS (Government of India, 2016)

tially established as a rationing system by the British Government during World War II to ensure workers in a few urban centers received food supplies (Nawani, 1994). The program later evolved in the early 1970s, as a welfare program with a primary objective to provide food security to vulnerable households, with the advent of green revolution and growth of domestic supply. Since its development as a welfare program, the PDS has been the primary policy to address food security in India.

The PDS supply chain is organized around the Food Corporation of India (FCI), a central government agency that procures food grains directly from farmers and stores them in government operated warehouses. The FCI then sells grain stocks to state governments who distribute them to retail outlets known as fair price shops. The fair price shops sell the grain to holders of ration cards. There are three broad classes of ration cards that are allocated based on a state's poverty line : Above Poverty Line (APL), Below Poverty Line (BPL), and Anthodaya Anna Yojana (AAY). The Anthodaya Anna Yojanaa (AAY) is a central government scheme started in 2000 that identifies the poorest of the poor households from amongst the BPL population. Extremely vulnerable households headed by widows, disabled, or destitute households with no assured means of subsistence are identified as AAY.

The value of PDS benefits are targeted towards the poor and hence is the lowest for APL households and highest for AAY households, where the central government assures AAY households a minimum PDS quota of 35kg of rice and/or wheat. The PDS benefits for AAY households has been constant and uniform across all states since its introduction in 2002. The benefits for BPL households, which form the majority of the population receiving PDS, differ across states and have increased over time. The PDS subsidy for BPL households differ by state as the fiscal expenditures towards the PDS are borne both by the central and state governments The difference between FCI's cost of procuring food grains from farmers and the price at which the supplies are sold to the states, also called as the central issue price, is subsidized by the central government. The state governments can further boost the subsidy by providing an additional discount over the central issue price or by increasing the central issued quota. Not all states provide an additional subsidy. The final subsidy is therefore the sum of central and state's outlays on PDS and differs across states as it depends on the state's outlays on PDS.

In the pursuit of food security, the Indian central government substantially increased the outlays on the PDS program under the National Food Security Act in 2013. The Act mandated that the food grains under the PDS be converted to a legal "entitlement" for beneficiaries (or the "right to food") (NFSA, 2013) and the onus was on the State governments to enforce and provide the food entitlements. The NFSA prescribed a national standardized minimum entitlement of 2kg rice and 3kg of wheat per individual at Rs 3/kg and Rs 2/kg respectively. The adoption of NFSA by states, however, was not uniform, as NFSA permitted states to continue their state-specific PDS programs (Gulati and Saini, 2013)). Therefore, since 2013, due to renewed political interest, several state governments significantly expanded their PDS programs either under NFSA or through their own state-level PDS programs such as Karnataka, Maharashtra and Bihar, whereas other states such as Gujarat did not expand. These expansions in the PDS program, were either through increase in PDS quota or a decrease in PDS price, hereafter jointly referred to as PDS entitlements.

2.2.1 Expansion in PDS Entitlements

During our time frame, certain states expanded their PDS entitlements for the BPL population, either by increasing the rationed quantity of grain or by reducing the subsidized price. In total, there are 11 policy changes in the PDS entitlements that correspond to the eight states in the ICRISAT data. Appendix Table A1 cleanly organizes and documents these changes.

Figures 1 and 2 show that several states substantially increased PDS grain quota entitlements and decreased PDS grain prices shortly after NFSA was passed. Among the eight states, the NFSA was first implemented in Maharashtra and Bihar in February 2014 and later in Madhya Pradesh from April 2014. In addition to the phased rollout of the NFSA, Karnataka expanded its PDS subsidy by initiating its own state-level PDS programs. In June 2013, the chief minister of Karnataka introduced the "Anna Bhagya Scheme", essentially doubling the PDS entitlements. Similarly, the chief minister of Madhya Pradesh introduced the "Mukhyamantri Annapurna Scheme" in June 2013, thereby reducing the PDS price entitlements to Re 1/kg for wheat.

Among all the eight states, Jharkhand had the most generous entitlement of 35 kg of rice per household at Re. 1/kg. whereas Gujarat had the least entitlement of 17 kg of rice and wheat per household. Also, these states did not implement any changes in the PDS policy rules. In contrast, Karnataka had the most significant increase in PDS entitlements in June 2013 with the introduction of Anna Bhaghya Scheme, followed by Maharashtra and Bihar in Feb 2014 with the introduction of NFSA.

In Appendix B, we show that these policy changes were actually implemented and the intended beneficiaries received a significant portion of their entitlement.

2.3 Theory

In the most common form, the PDS Subsidy is offered to beneficiary households through a fixed quantity of staple cereals (Q_0) at a subsidized price cp(where p is the market price of staples and $c < 1$).[10] In this scenario, according to the canonical model of consumer choice Southworth (1945), as shown in Figure 1, the original budget line AB reflects the trade-off between staple and non-staple consumption and is shifted out by the amount of the subsidy (Q_0) leading to the kinked budget constraint ACB. The slope of AC depends on the extent of price discount, that is, if staples are provided for free, as in a take it or leave it program, then AC would be flat. The budget line would shift to ECD for an equal valued cash transfer. Lastly, if staple cereals can be resold in the market, the budget line would be FCD and would depend on the resale price of PDS cereals.

Household I is better off under the in-kind subsidy as the PDS rationed quantity is unconstrained or infra-marginal, that is, staple cereal consumption is more than what is provided by the PDS. However, household II is weakly worse off under in-kind subsidy than under the equivalent cash transfer, as it prefers non-staples relative to staples, and would be constrained to choosing point C (the kink) if resale is unavailable and segment FC if resale is costly, while it would have chosen segment EC under the cash transfer.

[10]PDS price subsidy is a fixed price that is independent of the market price and is not a percentage subsidy.

2.3.1 Expected Effect on Dietary Diversity

If the PDS subsidy is extra-marginal and binding, then the subsidy would have no effect on non-staple consumption. For example, suppose the extra-marginal household II does not desire staples at all and consumes at the extreme pt. A in the original budget line, then with the PDS subsidy and no resale, household II would be "force-fed" staple cereals and staple cereal consumption would increase one-to-one with PDS grains.

If the PDS subsidy is infra-marginal, then the transfer is a pure income effect and as a result the consumption outcomes would depend on the income elasticity of the PDS staple cereals. In Figure 1, the infra-marginal household I can choose either of the four points W, X, Y and Z on the smooth part of the budget line CD, depending on the income elasticity of staple cereals. Point Z would be preferred if staple cereals are extremely income elastic ($\eta \gg 1$). In this highly improbable case, PDS subsidy will lead to an increase in PDS consumption only and no change in non-staple consumption. In contrast, if staple cereals are extremely income inelastic ($\eta \approx 0$) then point X would be desired. In this case, PDS Subsidy will lead to an increase in non-staple consumption and the beneficiary would simply reduce market (or out-of-pocket) purchase of staple cereals one-to-one with the amount of subsidy. Another case could be if staple cereals are inferior goods. In this paradoxical case, point W would be chosen and PDS subsidy would lead to a decrease in staple cereal consumption. Lastly, point Y would be desired if staple cereals have a non-negative income elasticity ($0 < \eta < 1$). In this case, PDS Subsidy would increase both staple and non-staple consumption.

Based on this simple model, there can be two probable cases wherein the PDS Subsidy would lead to an increase in staple consumption only, or "crowd-out" consumption of nutritious food items, as argued by certain critics. Either staple cereals are highly income elastic (Pt. Z) or households are extremely constrained or extra-marginal.

Another pertinent case is when PDS grains can be resold in the market. As PDS subsidy is non-binding, beneficiaries have an incentive to sell or trade it away, especially when they strictly prefer higher quality grains over PDS.[11]

[11] During our field visits in ICRISAT villages, we observed that a few large farmers in Andhra Pradesh, who were also producers of high quality rice, resold all their PDS rice to the market. They complained about the inferior quality of PDS rice and preferred to consume from their own production. In this case, even though the transfer of PDS

Under this scenario, if resale is costless, then PDS subsidy is the same as a cash transfer; consequently, consumption outcomes would depend on their respective income elasticities.

2.3.2 In-kind transfers and intra-household bargaining

The canonical Southworth (1945) model, as illustrated in Figure 1, predicts that an infra-marginal household is indifferent between transfer type. In other words, the marginal propensity to consume from in-kind and cash should be equal for infra-marginal households. But this hypothesis has been consistently rejected empirically in the context of the US food stamp program. Virtually every study finds that the marginal propensity to consume food out of food subsidy income is four to ten times higher than cash income (Fraker, 1990). In what follows, we argue that this empirical regularity is consistent with intra-household bargaining and heterogeneous preferences within the household.

The simple model described above is derived under the assumption that decisions are taken by a unitary household. However, if the consumption patterns are related to the interactions of more than one decision maker, then a unitary model may not be accurate. To deal with these issues, collective models are proposed (Browning and Chiappori, 1998), wherein a household maximizes the weighted average of utility functions of all household functions. Under this scenario, suppose women control food and men control non-food, then an infra-marginal in-kind transfer is akin to an implicit income transfer directed towards women. Such a targeted transfer might shift the weights in favor of women and therefore change the nature of the demand system, and consequently the propensity to consume food from the in-kind transfer may be greater than a similar valued cash transfer. This proposition has been conjectured by several researchers for the case of US food stamps, such as Senauer and Young (1986), Orazem (1999) and worked out in detail Breunig and Dasgupta (2005)

rice is less than their rice consumption, the subsidy may not be "infra-marginal" in the traditional sense. In contrast to large rice farmers, landless laborers and teachers in the same village consumed all their allotted PDS rice and had no complaints about the quality. They regularly cleaned and washed the PDS rice before consumption. In this study, we are unable to empirically examine resale or the role of the quality attributes of PDS grains, as these aspects are not recorded in the data.

2.4 Data

We use the new wave of ICRISAT's Village Dynamics in South Asia (VDSA) panel data of 1300 households observed over 60 months from June 2010 to July 2015.[12] The VDSA data cover 30 villages spread across eight states in India: Andhra Pradesh[13], Bihar, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra and Orissa. The geographical locations of the villages are shown in Appendix figure A1. Similar to the old VLS, households in each village are randomly selected to represent households in four land-holding classes: large, medium, small and landless.

The VDSA panel data are geographically divided into 18 villages in the Semi-Arid Tropics (SAT) and 12 villages in the Eastern region of India. The data follows the agricultural cycle in India from June to July. Endowment and household characteristics such as household size and landholding size are collected annually at the beginning of every panel year in June. Transactions, sales, market price, food and non-food expenditure data are collected every month. Market price data for commodities including rice and wheat are documented in the Monthly Price Schedule. Food expenditures are collected under the Transaction Module and are recorded item-wise along with information about the source of each food item, whether from home consumption or market purchase or from gifts. PDS rice and wheat are recorded as separate food items in the consumption module and are collected every month. Food consumption quantities and expenditures are converted into their nutrient content (calorie, protein and fat) using the nutrient value of Indian food items, based on (Gopalan et al., 1991).

[12]ICRISAT's Village level studies (VLS) are longitudinal surveys collected between 1975 to 1985 in six villages in the semi-arid tropics of India. Data collection was restarted from 2001 in the same six villages, tagged as the second generation of VLS (VLS2). However, the frequency of household surveys from 2001 to 2004 was limited to annual observations based on the availability of funds, and was increased to monthly data in 2005-06. It was only after 2009, with the funding from the Gates foundation, the VLS was expanded significantly and was renamed as the Village Dynamics in South Asia (VDSA). In 2009, 12 villages in the semi-arid tropics, in addition to the 6 old VLS villages, and 10 more villages from east India were included; summing to a total of 30 villages across India. The data for panel year 2009, however, has many gaps, especially in the consumption module, and is inconsistent with the subsequent panel years. Accordingly, this paper uses data beginning from panel year 2010 until 2014.

[13]Two villages are in Telangana, a state formed in 2014. As our dataset begins before the formation of the new state, and for the purpose of consistency, the 2 villages in Telangana are considered as Andhra Pradesh

Households' ration card status is collected differently depending on geographical region. In East India, ration card status is reported in the General Endowment Schedule (GES), and is collected at the beginning of every panel year in June. In the Semi-Arid Tropics, ration card status is collected during two periods - the beginning of panel year in 2009 and during a Household Census Survey (HCS) in 2014. Comparison of the ration card status between the two-time periods, show that few households change their ration card status over the period of observation. We therefore use a time-independent ration card status of households in 2009 for SAT villages and 2010 for East India villages, over the entire sample period. All the 30 villages have a fair price shop. The corresponding author of this study visited most of these SAT villages in person and conducted extensive fieldwork. The operation of PDS ration shops in each village, validation of ration card status and perception of PDS among beneficiaries were documented.

Table 1 shows the summary statistics. We drop households with less 48 months of data and households whose head lives outside the village. The final sample consists of 1217 households.

A few caveats are in order regarding the ICRISAT data. First, the data is not representative at the national level, state or district level. However, the summary statistics from the ICRISAT are consistent with the nationally representative sample from NSSO. For instance, based on most recent round of NSSO in 2011-12, the national average per capita per day calorie consumption was 2233 Kcal, protein intake was 60.7gms and fat intake was 46 gms (NSSO, 2014), which are comparable with the summary stats reported in Table 1. Second, the data sample is primarily focused on small holder farmers in rural and impoverished regions and may not cover all types of households. For instance, migrant households or households in remote areas who find it more difficult to access the PDS; or female-headed households for whom PDS may have larger effects.

2.5 Methodology

2.5.1 PDS transfer value

Following Kochar (2005), Kaushal and Muchomba (2015) and Kaul (2018), we quantify the increases in the generosity of the PDS subsidy by considering the transfer value,[14] calculated as the product of the quantity and the price discount (difference between the market and PDS price):

$$Subs_{hst} = \overbrace{Q_{hst}^{pds\,rice}\left[\overline{P}_{s}^{Market\,rice} - P_{hst}^{pds\,rice}\right]}^{RiceSubsidy} + \overbrace{Q_{hst}^{pds\,wheat}\left[\overline{P}_{s}^{Market\,wheat} - P_{hst}^{pds\,wheat}\right]}^{WheatSubsidy} \tag{2.1}$$

where Q_{hst}^{pds} is the statutory PDS quota set by state s for household h in month t, $\overline{P}_{t}^{Market}$ is the average market price over the sample period in state s and P_{hst}^{pds} is the statutory PDS price set by state s for household h in month t. The market price data comes from the Price Schedule in the ICRISAT data and corresponds to a comparable variety of PDS rice and wheat.

We use the state-level average market price to avoid endogeneity of market prices to the PDS subsidy. For instance, it is possible that an expansion of the PDS subsidy leads to a decrease in market prices, since PDS and non-PDS grains are close substitutes. Our measure of PDS entitlement is a function of only three sets of variables: household ration card status, household size, and state-level statutory entitlements . This ensures that any variation in the subsidy measure is derived solely from changes in the PDS program parameters (or “entitlements”), not changes in market conditions, or household consumption.

Figure 3 shows the changes in the PDS subsidy value in each state. The figures 1, 2 and 3 together show that there is tremendous variation, both temporally and spatially, in the PDS program parameters.

[14] Measuring the generosity of PDS subsidies in terms of their implicit transfer value is valid if the subsidized amount is infra-marginal, so that consumption of staple cereals is more than what is provided by the PDS. Our data suggests that this is generally the case for households in our sample. The average household in our data consumes 48kg of staple cereals as compared to a maximum of 35kg of grains per household provided by the PDS. None of the households get all their staple cereals from the PDS in a given month.

2.5.2 Regression Framework

The effect of PDS on nutrition is estimated using fixed effects:

$$Y_{hst} = \alpha_h + \lambda_t + \delta_h t + \beta_1 Subs_{hst} + \epsilon_{ist} \tag{2.2}$$

where Y_{hst} is the outcome variable (such as staple cereal consumption, consumption of other food items, calorie and nutrient consumption etc.) for household h, in state s and month t and $Subs_{hst}$ is the implicit subsidy value defined in (3.1). Variables α_h and λ_t are the household and time fixed effects and δ_h is the household-specific time trend. Standard errors are clustered at the village level. The consecutive month fixed effects λ_t absorb any aggregate time shocks that affect consumption, including any price effects or changes in the government procurement pricing policies.

The model exploits both cross-sectional and temporal variation in the PDS program. The temporal variation comes from the 11 policy changes in the PDS entitlements during the study period. The cross-sectional variation comes from the difference in PDS entitlements across states and the differential expansion in the PDS entitlements for BPL households. The above fixed effects specification is akin to a triple difference methodology, wherein the first difference is between households who were exposed to a more generous and a less generous PDS expansion the second difference is between households before and after the PDS expansion and the third difference is between beneficiary (BPL) and non-beneficiary households (APL or No card).

2.6 Results

2.6.1 Effect on nutrition

We estimate the direct effect of PDS on staple cereals consumption and the indirect effect on non-subsidized food items, both in terms of quantity and value. Table 2.2 presents the coefficient estimates on the PDS subsidy value β_1 . Each co-efficient estimate comes from a separate estimation of equation (3.2) with different food types as outcome variables. Standard errors are clustered at the village level. To interpret the significance of the estimates, we hereafter consider a policy experiment of increasing the PDS subsidy value by 100 rupees per adult-equivalent per month - an amount equivalent to the PDS expansion in Karnataka in June 2013.

As shown in Table 2.2, we further segregate total consumption of staple cereals based on the source of supply; whether from home production or purchased from market or the PDS shop or a combination thereof. The results for total consumption quantities clearly show that a more generous PDS subsidy increases total staple cereal consumption: 100 rupees in PDS subsidy value translates to 2.9 kg increase in staple cereal consumption (2kg rice and 0.8kg wheat), all measured in all measured in monthly per-adult equivalent scale. As one might expect, this increase in total staple cereal consumption is primarily a result of increased consumption of grains from the PDS: A 100 rupees increase in PDS subsidy value translates to 3.2 kg increase in PDS rice and wheat consumption (2.3kg rice and 0.9kg of wheat). Consistent with the prediction that PDS subsidy decreases out-of-pocket expenditure on staples, we find that the quantity of staples sourced from the market decreases: 100 rupees increase in PDS subsidy translates to 0.4kg decrease in staple cereal quantity purchased from market, all measured in monthly per-adult equivalent. Results for expenditure values are consistent with quantities. Expenditure on staple cereal consumption decreases, with greater decline in market purchase.

Table 2.2 also presents the indirect effects of PDS on the consumption of food items other than staple cereals, both in terms of quantity and value. Here, only consumption from all sources (Purchase + Home + Gifts) is considered. For vegetables and fruits only expenditure values are considered as data on quantities are not available for the first three panel years in the ICRISAT data. The results for consumption quantities show that a more generous PDS subsidy increases total consumption of pulses, milk and milk products, sugar and oils: 100 rupees increase in PDS subsidy translates to an increase of 205gms in total pulse consumption, 779gms in milk and milk products and 185gms in sugar and 200gms in oils consumption. The results for expenditure values shows that PDS increases expenditure on pulses, milk and milk products, fruits, vegetables, sugar and spice, other food items (that include beverages, bread, biscuits and savories) and meals consumed outside. Altogether, PDS significantly improves total food consumption, especially through purchases from market.

Table 2.3 presents the main results of this paper on the overall nutritional impact of PDS, in terms of calorie, protein and fat intake. We separately examine the energy and macronutrient intake sourced from all food types, from staple cereals (further segregated into those sourced from PDS versus the market) and from non-staple food types. Not surprisingly, the most significant amount of calories are derived from the PDS ration shop: A 100 rupees monthly increase in PDS subsidy translates to 374kcal daily per adult equivalent increase in energy intake. These results are consistent with the increases in consumption quantities reported in Table 2.2.[15] Consumption of calories and macronutrients from staple food other than PDS decrease, and this decrease is compensated in greater magnitude by an increase in calorie and nutrient intake from other food types. A negligible 0.4kcal drop in calories from non-PDS staple cereals is substituted by 2.3kcal increase in calorie intake sourced from other food items including 0.2kcal each in pulses, milk and milk products, oils, sugar and 0.1kcal from fruits. As a result, consumption of more nutritious foods purchased from the savings from the PDS subsidy significantly increases intake of overall calorie, proteins and fats: A monthly increase of 100 rupees in PDS subsidy translates to 449kcal increase in energy intake, 10.9 grams increase in protein intake and 8.5 grams increase in fat intake, all measured in daily per adult equivalent.

Overall the results in Tables 2.2 and 2.3 suggest that PDS substantially improves nutrition and dietary diversity. In addition to an increase in staple cereals, consumption of diverse food types including pulses, milk and milk products, oils, vegetables, fruits and sugar increases. Consequently, the overall calorie, protein and fat intake increases. Hence, the results clearly show that PDS "crowds-in" consumption of nutritious foods.

These results also throw light on the channels through which PDS may affect household consumption and spending patterns. An important consumption pattern, implied by an increasing trend on the proportion of staple

[15]The disaggregated results for rice and wheat, reported in Appendix Table 3 imply that a monthly increase of 100 rupees in PDS subsidy value translates to a 2.3kg increase in PDS rice and 0.9 kg increase in PDS wheat monthly consumption per adult-equivalent. In the NSSO nutrition chart NSSO (2014), based on the nutrition values provided in Gopalan et al. (1991), the daily calorie equivalent of 1 kg of rice and wheat is 3460 Kcal and 3410 Kcal respectively. Therefore, assuming 30 days in a month, 2.3kg monthly increase in PDS rice is equivalent to 265Kcal per day (=3460*2.3/30) and 0.9kg monthly increase in PDS wheat is equivalent to 102Kcal per day (=3410*0.9/30). Hence the total increase in daily calorie intake from a monthly increase of 100 rupees in PDS subsidy value approximately equal to 367Kcal.

cereal consumption from PDS, is that households cash-out part of the in-kind PDS subsidy by reducing their market purchases. As a result, PDS provides significant savings to intended beneficiaries. In addition to the amount saved from buying from the PDS ration shop instead of the market, reductions in purchases from the market further add to their savings. These savings from PDS may unbind liquidity constraints and subsequently increase purchases of other food items and non-food items. Hence, in this manner, PDS provides more flexibility in consumption patterns for beneficiary households, who benefit not only from the provision of subsidized cereals but also in terms of overall food and nutrient intake.

2.6.2 Elasticities and marginal propensity to consume with respect to PDS subsidy value

We assess the magnitude and significance of our results on the nutritional impact of PDS, by comparing our estimates with past research on food subsidies and with respect to fungible income sources observed in our dataset. We follow the standard procedure in the food subsidy literature and compute elasticities and MPC with respect to both PDS subsidy value and total expenditure or cash income. While the estimations on cash income in this study are not experimentally identified, there are several reasons that validate this approach. First, the literature on US food stamps extensively use household income as a proxy for cash income (Hoynes and Schanzenbach, 2009; Beatty and Tuttle, 2015; Fraker, 1990). Second, expenditure elasticity of calorie intake and MPC food out of total expenditure are widely studied and estimated parameters (Deaton and Muellbauer, 1980; Strauss and Thomas, 1995; Subramanian and Deaton, 1996). Nonetheless, we are cautious in interpreting the estimations as causal for total expenditures and income. The idea of this exposition is to determine whether the nutritional improvements from PDS found in this study is larger than previous estimates or alternative sources of fungible income.

Specifically, we estimate MPC food and non-food expenditures and elasticities of calorie, proteins and fats; all with respect to PDS Subsidy and total expenditure value. Lastly, we compute elasticities with respect to benefits received from other government schemes such as middaymeals, pensions, scholarships, NREGA and also with respect to different sources of income.

Table 3.4 shows the MPC food and non-food expenditures with respect to PDS Subsidy value in Panel A and total expenditure in Panel B. Disaggregated results by food type are reported in Appendix Table A3. The results suggest that a significant proportion of PDS Subsidy income is spent on food expenditures, whereas only a small proportion of total expenditure is spent on food. An increase of 100 rupees in PDS subsidy translates to 84 rupees increase in food expenditure, out of which 36 rupees is spent on market purchases, all measured in monthly per-adult equivalent scale. In other words, 84% of the PDS Subsidy income is spent on food. Conversely, only 12% of total expenditure is spent on food and 84.5% is spent on non-food.[16] Therefore, the results imply that the MPC food from PDS Subsidy is about 6.5 times MPC food from total expenditures. These results are consistent with the empirical findings on the US food stamp program, that the MPC of food from food stamp income is four to ten times that of cash income.

We also estimated MPC calories, proteins and fats with respect to total expenditure value. Results are reported in Appendix table A4. The MPC nutrients out of PDS Subsidy (shown in Table 5) is considerably greater than the MPC nutrients out of expenditure: about 15 times greater for calorie intake, about 13 times greater for total protein and about 8 times greater for fat intake.

To compute elasticities, we estimate equation (3.2) in the log-log form and thereby limit the sample to BPL households with a non-zero PDS subsidy value in all the estimations.[17] Table 2.5 lays side-by-side the estimates of subsidy elasticities in Panel A and expenditure elasticities in Panel B; we separately examine the intake of calories, proteins and fat sourced from all food types, segregated into staple cereals and from non-staple food types. The results for disaggregated food types are reported in Appendix table A5.

All the elasticity estimates in both Panels A and B are positive and signif-

[16] Our estimate of MPC food out of total expenditure (0.12) is within the estimates found in previous studies ranging from 0.03 to 0.17 (Fraker 1990, Deaton and Muelbauer 1980; S. Souleses 1999; Blanciforti and Green 1983). We are however, not able to compare our estimates with more rigorous randomized controlled experiments, as most of these studies report the treatment effects of the program, rather than the dollar value on food expenditures (Attanasio, Battisin, Mesnard 2011; Cunha 2014)

[17] To ensure comparability, we do not consider the entire sample size in estimating expenditure elasticities. Although, the expenditure elasticities are similar over the entire sample of households and for PDS beneficiary HHs.

icant. The subsidy elasticities of calories, proteins and fat intake from total food consumption are comparable to expenditure elasticities. Not surprisingly, the magnitude of the subsidy elasticities is greater for staple foods and smaller for non-staples; although, it is important to note that the magnitudes on non-staple consumption are positive and large. The estimated elasticity of the overall calorie intake with respect to the value of the PDS subsidy in this study is 0.285 and is significantly larger than previous estimates: 0.144 in Kaul (2018), 0.06 in Kochar (2005), -0.003 and statistically insignificant in Kaushal and Muchomba (2015).[18] One of the possible reasons for a higher estimate in this study could be the inclusion of non-marginal expansions in the PDS program, post-NFSA. Hence, the results suggest that the percentage change in the overall calorie and protein intake in response to a one percent change in total expenditure value is at best equivalent if not better than a one percent increase in the PDS subsidy value and the response on staple cereal consumption is markedly greater with PDS subsidy value.

To further investigate the significance of the PDS subsidy elasticities, we compute elasticities with respect to benefits received from other government schemes and different income sources.[19] Table 8 presents the elasticity estimates for total food consumption. The elasticity estimates for middaymeals are the highest, followed by pensions, in comparison to all other government benefit programs. These results are consistent with previous studies that show positive nutritional impact of midday meals (Afridi, 2010). Among the different sources of income, elasticities with respect to farm wage income, followed by income from credit, are greater.

Overall, our results suggest that elasticities with respect to PDS subsidy value are comparable to expenditure elasticities and are substantially larger than previous estimates. In addition, we show that most of the PDS subsidy income (84%) is spent on food, against non-food. Although, comparing the elasticity and MPC estimates from PDS subsidy and cash income are fairly speculative, the results provide suggestive evidence that the effect of PDS on

[18] However, the estimated expenditure elasticity in this study (0.235) is slightly less than previous estimates: 0.34 in Subramanian and Deaton (1996), 0.3 in Strauss and Thomas (1995), 0.24 in Kochar (2005).

[19] Benefit values for middaymeals, pensions and scholarships in the ICRISAT data are collected on a monthly basis in the Transaction Schedule only for 18 villages in the SAT region. Furthermore, it is important to note that the value of pensions is reported by households and the value of middaymeal is imputed by the ICRISAT field investigators.

nutrition may be greater than predicted by an assumption of fungible income sources.

2.6.3 Robustness Tests

We test the robustness of our main results on energy and nutrient intake to specifications that control for a more constrained set of fixed effects and trends. Tables 2.7, 2.8 and 2.9 report the robustness test results for calorie, protein and fat intake respectively. We further limit the data sample to BPL households and perform the same robustness tests. Results for the full sample are reported in Panel A and for BPL households in Panel B.

As shown in Panel A in Table 2.7, the effect of PDS subsidy on calorie intake is robust to a series of constrained specifications. The significance of the estimates remain the same even if the standard errors are clustered at the state-level. The results are robust to including state or village-by-month fixed effects that control for any state or village-level factors that may potentially influence both PDS subsidy and household consumption, and to a more constrained specification of controlling for state or household-specific trends. Lastly, we test the parallel-trends assumption, by including a one-year lead of the PDS subsidy value in the fixed-effects estimation. The coefficient estimate on the lead subsidy is insignificant, and thus validates our difference-in-difference strategy. Similarly, the results for protein and fat intake reported in Tables 2.8 and 2.9 and those for BPL households in Panel B are robust to the same specification tests.

Table 2.10 presents a series of further robustness checks. To address concerns of possible endogeneity of market price or household size, we fix the state-average market price and household size to pre-2013 levels. The results reported in Table 8 show that the results are qualitatively similar to the main results, though using a nominal subsidy value makes the estimates appear smaller.

Finally, to address concerns of any confounding effects of the PDS with other government welfare programs, we utilize the available data in the ICRISAT on government benefits received by each household. We estimate the effect of PDS subsidy value on government benefit values received in a regression that controls for household and time fixed effects, similar to equation (2). Results, reported in Table 2.11 suggest that expansions in the PDS program had no effect on the receipt of benefits from other welfare schemes such as Midday meals, NREGA, Pensions and Scholarships and relied loans. Furthermore, we specifically test for confounding effects of the PDS with NREGA and test whether our main results on calorie and nutrient intake are robust after controlling for state-level NREGA policy changes, such as fiscal allocations and implementation. Specifically, we estimate equation (2) controlling for an interaction term of state-level NREGA control interacted with ration card status of the household. Results from this specification, reported in Table 2.12, suggest that the co-efficient estimates are qualitatively similar to our base specification.

2.7 Role of Intra-Household Bargaining

According to the theoretical implications of a collective model, discussed in section 3.2, the expected effect of PDS on food consumption would be greater in households where women have greater control over the food budget. To test this proposition requires variation in the level of bargaining power specific to the food budget.

We utilize the available information in the ICRISAT data on the role of gender in decision-making, as a measure of intra-household bargaining. The questionnaire on role of gender in decision-making covers important decisions related to utilization of households resources such as assets, inputs, outputs and other miscellaneous resources; and whether the decision is taken by men, women or both. Summary statistics of decision variables for BPL households are reported in Table 2.13. The statistics are arranged by gender, the columns represent the percentage of households that fall in each category of decision making and the rows represent the type of household resources. The proportion of households where women take decisions is minimal for most of the household resources, except for household maintenance. This suggests that, in the ICRISAT data, most of the resource allocations are either jointly decided by both genders or are decided by men only.

In this study, based on the information in the ICRISAT data, we consider gender control of "household maintenance" decisions as the most appropriate proxy for bargaining power over food-related decisions. Although household maintenance may include resources in addition to food, it is the best possible measure of intra-household bargaining over food available in our dataset. Furthermore, we are unable to test the proposition that PDS may have larger effects on female-headed households, as the proportion of female-headed households in our dataset is less than 10%.

We conduct a weak-test on whether intra-household bargaining can promote food consumption out of PDS Subsidy, as compared to non-food consumption, by considering the interaction between PDS Subsidy value and intra-household bargaining measures,

$$Y_{hst} = \alpha_h + \lambda_t + \delta_h t + \beta_1 IB_{ht} + \beta_2 Subs_{hst} + \beta_3 IB_{ht} Subs_{hst} + \epsilon_{hst} \tag{2.3}$$

where α_h and λ_t are household and time fixed effects respectively, δ_h is the household-specific time trend. IB_{ht} is a categorical variable that measures intra-household bargaining, where $IB_{ht} = 1$ if female decides, $IB_{ht} = -1$ if male decides and $IB_{ht} = 0$ if both decide. As the marginal effect of PDS Subsidy when female decides household allocations is $\beta_1 + \beta_3$, the coefficient β_3 can be interpreted as the extent to which intra-household bargaining assists the impact of PDS on nutrition and hence is the coefficient of interest. $\beta_3 > 0$ for food consumption outcomes and $\beta_3 < 0$ for ill-favored non-food consumption outcomes, imply that intra-household bargaining facilitates food consumption from PDS Subsidy. In addition to using household maintenance, we estimate (3.3) using the other decision variables on assets, inputs and outputs as a robustness test to show that the effect of PDS on food is specific to women's control over food-related decisions and may not be generalized to "women's empowerment".

The results from estimating equation (3.3) are provided in Table 2.14. As proxies for intra-household bargaining, relevant for consumption outcomes, we consider the role of gender in decision making related to household maintenance, crop production, sale and use and credit management. Panel A, B and C report the three measures of intra-household bargaining. The interaction terms on nutrient intake are positive for all three intra-household bargaining measures, which imply that intra-household bargaining plays a facilitating role in improving nutrition through the PDS. Results on expenditures are consistent. As shown in Panel A, households where women decide on household maintenance spend 94% (= 0.78+0.16) of the PDS income on food expenditures, as against 62% (=0.78-0.16) when men decide. More importantly, expenditures decrease on temptation goods such as alcohol and cigarettes and other non-essentials like cell phone use. On the other hand, expenditures on energy and children's education increases.

Overall, the results are consistent with a model in which some households treat resources as not completely fungible across food and non-food budgets. As a result, households in which women control the food budget spend the PDS transfer predominantly in the form of food and other items preferred by women.

2.8 Conclusion

In this paper, we examine whether the world's largest in-kind food subsidy program - India's PDS - improves household nutrition. Using state-level changes in the program that occurred after the National Food Security Act of 2013, we show that increases in the generosity of in-kind staple food transfers substantially improved nutrition In particular, staple food subsidies "crowded-in" consumption of diverse food items, and consequently increased food consumption in terms of quantities and total calorie, protein and fat intake. Our results suggest that households reduce market purchase of staple cereals and use the extra saving to purchase more nutritious food such as pulses, milk and milk products, fruits and vegetables. These results imply that PDS provides more flexibility in consumption patterns for beneficiary households, who benefit not only from the provision of subsidized cereal but also in terms of overall food intake.

Furthermore, we find that PDS beneficiaries consume 84% of the subsidy's transfer value in the form of food, suggesting that the transfer does not cause them to substantially reduce their expenditures on non-subsidized food. We argue that intra-household bargaining may explain these results, as we find that households where women decide on resource allocations spend greater proportion of their PDS income on food expenditures.

Our results have important implications for the Indian policy debate around the effectiveness of the NFSA and the PDS program. The PDS has been criticized on the grounds that the program is poorly targeted, does not reach the intended beneficiaries and hence may have little impact on nutrition. Furthermore, critics contend that PDS encourages only "empty calories", and thus may crowd-out more nutritious food items and not improve dietary diversity(Desai and Vanneman, 2015; Gulati et al., 2012). Our results suggest that these criticisms are not generally valid. Given the constraints of our study area, our results show that the NFSA and state-level PDS initiatives effectively reached the intended beneficiaries and had a positive impact on household nutrition.

As an alternative to PDS, many policy makers have suggested a replacement of PDS with cash transfers. Although in theory, cash transfers are more efficient, the PDS has an intricate political economy in reform that garners huge political support and is often featured in election manifestos. As a consequence, many state governments have focused on improving the efficiency of the PDS program and have refrained from any form of replacement and no state government in India has showed interest in replacing PDS with cash transfers. Only three union territories, administered by the central government, implemented direct benefit transfer program on a pilot basis starting in September 2015. However, preliminary assessments suggest that implementation quality remains an issue (only 65-67% of beneficiaries reported received cash benefits) and that it costs beneficiaries more to collect their cash benefits than collecting food rations (Muralidharan et al., 2017).

Therefore, in light of the debate over the effectiveness of PDS, our results suggest that PDS is an effective tool in addressing household nutrition in India and any replacement of the PDS program demands careful consideration.

2.9 Figures and Tables

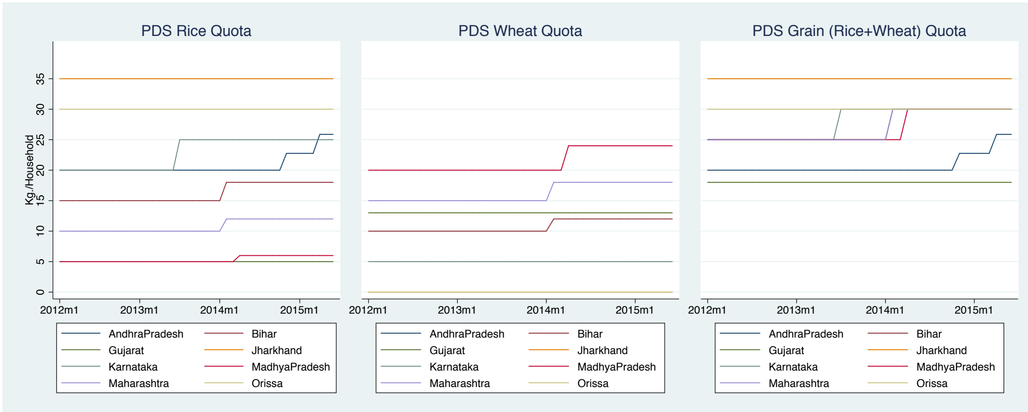


Figure 2.1: PDS quantity entitlement for BPL households from 2012 to 2015

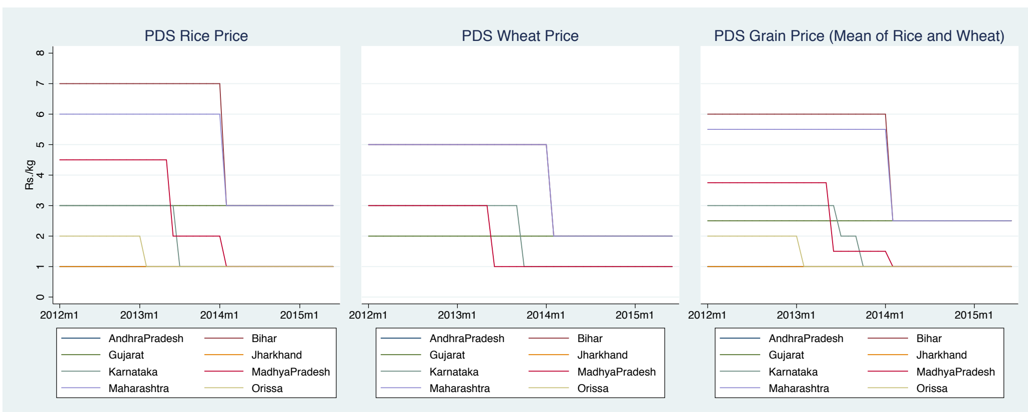


Figure 2.2: PDS price entitlement for BPL households from 2012 to 2015

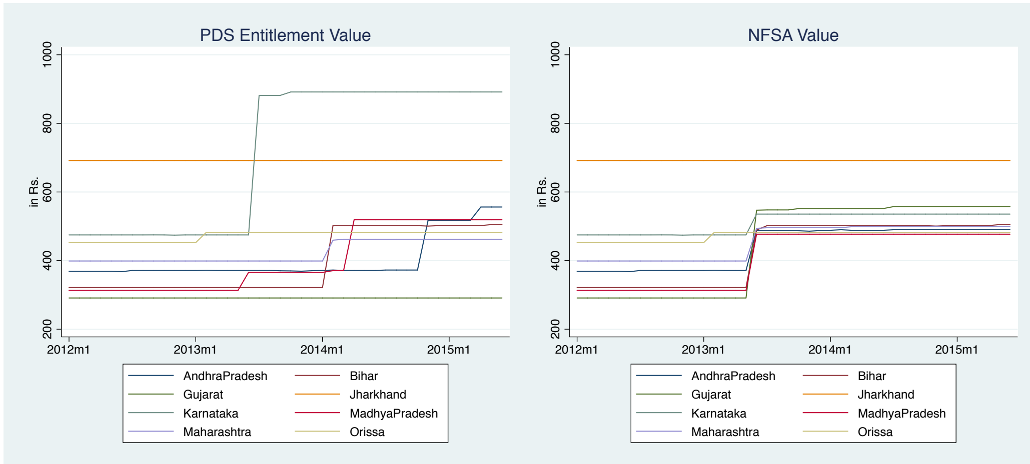


Figure 2.3: PDS implicit subsidy entitlement for BPL households from 2012 to 2015

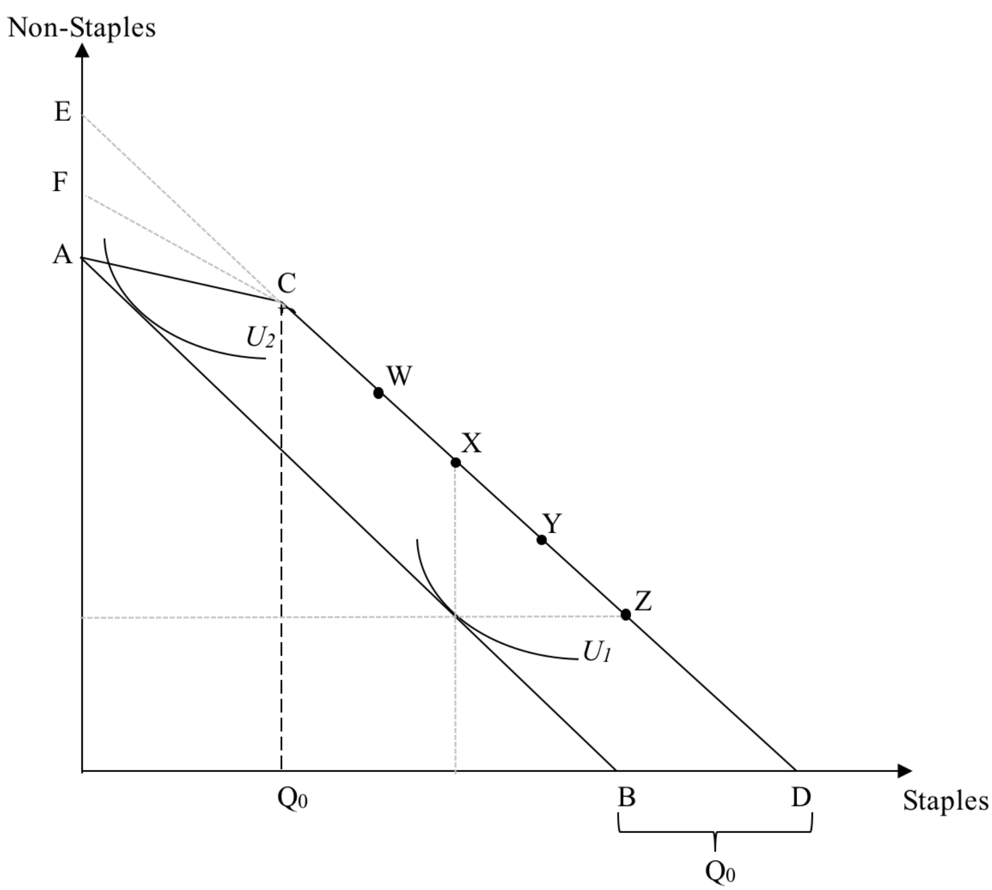


Figure 2.4: In-kind staple food vs Non-staple consumption

Table 2.1: Summary Stats

	AAY	BPL	APL/NoCard	Total
Number of HHs	105	579	533	1217
Number of members in the HH	4.706	4.724	5.040	4.861
	(2.125)	(2.238)	(2.377)	(2.296)
Nutrient and Calorie intake				
Calorie intake (Kcals)	2115.7	2032.5	2009.1	2029.7
	(740.9)	(794.8)	(746.3)	(770.1)
Protein intake (gms)	56.61	52.06	54.04	53.31
	(22.43)	(21.92)	(21.18)	(21.69)
Fat intake (gms)	39.21	37.92	46.74	41.84
	(19.53)	(35.99)	(25.96)	(31.07)
Consumption Quantity (in Kgs)				
Total Staple Cereals	12.82	11.46	10.43	11.13
	(5.886)	(5.546)	(5.608)	(5.648)
Quantity of pds grain consumed	7.259	5.400	1.183	3.742
	(3.905)	(3.883)	(2.511)	(4.067)
Pulses	1.066	1.035	0.964	1.007
	(0.704)	(0.811)	(0.677)	(0.748)
Expenditure and Income (in 2010 value)				
Food expenditure	558.2	596.7	715.6	644.7
	(236.4)	(305.3)	(359.1)	(330.6)
Non-food expenditure	518.7	667.3	757.5	693.4
	(1708.2)	(3221.9)	(3394.4)	(3197.9)
Total expenditure	1077.3	1264.7	1475.6	1339.4
	(1760.8)	(3278.9)	(3477.1)	(3267.4)
Implict PDS Subsidy	198.9	127.1	10.54	83.05
	(131.2)	(69.42)	(22.64)	(91.77)
Income total	1567.4	2243.5	2680.4	2375.9
	(4128.6)	(16946.8)	(13784.3)	(14878.5)

Standard deviation in parentheses. All values, except number of HHs and household size, represent the adult equivalent per household. Nutrient and Calorie intake is measured daily per-adult equivalent. Consumption quantity, expenditure and income is measured monthly per-adult equivalent.

Table 2.2: Impact of PDS subsidy on food consumption (N=69,846)

	Quantity (in grams)	Value (in 2010 Rs)
Staple Cereals (Rice and Wheat)		
All sources (Market +PDS+Home)	29.658***	-0.021
	(3.063)	(0.039)
Purchase from PDS only	32.891***	0.001
	(3.176)	(0.023)
Without PDS (Market + Home)	-3.208	-0.050
	(2.863)	(0.033)
Purchase from market only	-4.068***	-0.096***
	(1.408)	(0.034)
From Home production only	0.395	-0.008
	(2.489)	(0.037)
Other food types		
Pulses	2.047***	0.082***
	(0.364)	(0.022)
Coarse cereal	2.284	0.002
	(1.915)	(0.029)
Milk and milk products	7.794***	0.177***
	(2.733)	(0.063)
Fruits		0.026*
		(0.014)
Vegetables		0.121**
		(0.046)
Eggs	3.574*	0.011
	(2.024)	(0.007)
Meat	0.114	0.018
	(0.434)	(0.047)
Sugar and spice	1.846**	0.064**
	(0.836)	(0.025)
Oils	2.009***	0.104***
	(0.508)	(0.025)
Other food items		0.188***
		(0.042)
Meals outside		0.146**
		(0.059)

Standard errors in parentheses are clustered at the village level. * $p<0.10$ ** $p<0.05$ *** $p<0.01$. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor and different food categories as outcome variables.

Table 2.3: Effect of PDS subsidy value on energy and nutrient intake (N=69846)

	Energy (Kcal)	Protein (mg)	Fat (mg)
Total Food	4.488***	109.343***	85.646***
	(0.605)	(15.802)	(17.725)
Non-staple food	2.289***	50.799***	100.634***
	(0.491)	(11.860)	(21.005)
Staples (Rice and wheat)	3.409***	87.725***	8.474***
	(0.353)	(9.874)	(1.293)
Staples from PDS	3.784***	96.886***	9.280***
	(0.364)	(10.846)	(1.555)
Staples except PDS	-0.369	-9.025	-0.797
	(0.328)	(9.166)	(1.054)

Standard errors in parentheses are clustered at the village level. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor variable. Column heading represents consumption outcomes and row heading represents the source of consumption outcomes.

Table 2.4: MPC food and non-food, out of PDS Subsidy and total expenditure (N=69846)

	PDS Subsidy	Expenditure
Food expenditure		
Food total (Home+Purchase+gifts)	0.840***	0.121***
	(0.172)	(0.012)
Food total (without PDS and Midday meal)	0.865***	0.144***
	(0.213)	(0.015)
Food from purchase (with PDS)	0.419***	0.075***
	(0.147)	(0.010)
Food from purchase (without PDS)	0.364**	0.075***
	(0.138)	(0.010)
Food from home production	0.122	0.033***
	(0.089)	(0.005)
Non-Food expenditure		
Non-food total	0.116	0.845***
	(0.527)	(0.016)
Grinding and Milling expenditure	0.014**	0.001***
	(0.005)	(0.000)
Medical (domestic & hospital) expenditure	0.078	0.063***
	(0.072)	(0.006)
Educaton	0.050	0.062***
	(0.045)	(0.006)
Cell phone use	0.030*	0.005***
	(0.016)	(0.001)
Cosmetics	0.062***	0.006***
	(0.019)	(0.001)
Energy expenditure (LPG, kerosene)	0.013	0.004*
	(0.013)	(0.002)
Drugs (Alcohol, Toddy, Tobacco)	0.026	0.017***
	(0.051)	(0.002)
Travel (Petrol, vehicle, etc)	0.095	0.070***
	(0.067)	(0.012)
Clothes	-0.102	0.096***
	(0.097)	(0.008)
Ceremonies, marriage expenses	0.413	0.211***
	(0.455)	(0.015)

Standard errors in parentheses are clustered at the village level. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor and different food categories as outcome variables.

Table 2.5: Elasticities of energy and nutrient intake with respect to PDS subsidy value and expenditure (N=36,894)

	Panel A : PDS Subsidy			**Panel B : Total Expenditure**		
	Energy (Kcal)	Protein (mg)	Fat (mg)	Energy (Kcal)	Protein (mg)	Fat (mg)
Total Food	0.285***	0.273***	0.222***	0.211***	0.225***	0.271***
	(0.034)	(0.032)	(0.040)	(0.023)	(0.024)	(0.031)
Staple food (Rice and wheat)	0.317***	0.303***	0.284***	0.173***	0.179***	0.191***
	(0.045)	(0.047)	(0.055)	(0.022)	(0.024)	(0.029)
Non-staple food	0.220***	0.204***	0.215***	0.350***	0.384***	0.355***
	(0.044)	(0.045)	(0.048)	(0.034)	(0.037)	(0.031)

Standard errors in parentheses are clustered at the village level. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor and different food catogories as outcome variables.

Table 2.6: Elasticities of calories, proteins and fats with respect to other Income sources

	Kcal	Protein	Fat	N
Other Government benefits				
Middaymeals	0.114***	0.103***	0.087***	7961
	(0.014)	(0.014)	(0.013)	
Pensions	0.096***	0.098***	0.124***	5561
	(0.025)	(0.024)	(0.028)	
Scholarships and Relief	-0.001	0.000	-0.004	684
	(0.006)	(0.006)	(0.009)	
All benefits, expect PDS	0.014***	0.012***	0.016***	15381
	(0.003)	(0.003)	(0.003)	
Income sources				
Farm wage Income	0.029***	0.027***	0.015**	15184
	(0.006)	(0.006)	(0.007)	
Non-Farm wage Income	-0.007	-0.002	0.012	24218
	(0.006)	(0.006)	(0.008)	
NREGA wages income	-0.003	-0.007	-0.007	1643
	(0.010)	(0.010)	(0.010)	
Credit (formal and informal)	0.016***	0.016***	0.015***	4765
	(0.003)	(0.003)	(0.004)	
Loans (formal and informal)	0.009***	0.010***	0.007***	13314
	(0.002)	(0.002)	(0.002)	
Income from Crop and livestock	0.004	0.004*	0.008**	27656
	(0.002)	(0.002)	(0.003)	
Total Income	0.008***	0.009***	0.011***	29003
	(0.002)	(0.002)	(0.002)	

Standard errors in parentheses are clustered at the village level. * $p<0.10$ ** $p<0.05$ *** $p<0.01$. Each coefficient estimate is from a separate regression with row headings representing regressor variables in natural logarithm and column heading representing dependent variables in natural logarithm.

Table 2.7: Robustness Tests - Total calorie intake

	Energy Intake (Kcal)													
	Panel A: Full Sample							Panel B : BPL households only						
PDS Subsidy value	3.665***	3.665***	3.788***	3.814***	3.814***	5.018***	5.198***	4.344***	4.344***	5.163***	5.380***	5.375***	6.324***	5.168***
	(0.462)	(0.326)	(0.518)	(0.540)	(0.540)	(0.630)	(0.752)	(0.733)	(0.843)	(1.001)	(0.984)	(0.984)	(1.124)	(1.036)
Lead Subsidy value							0.140							0.051
							(0.245)							(0.290)
HH FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SE clustered at State-level		X							X					
State-month FE			X							X				
Village-month FE				X	X	X					X	X	X	
State trends					X							X		
HH trends						X	X						X	X
Observations	69846	69846	69846	69846	69846	69846	54857	34233	34233	34233	34233	34233	34233	26718

* p<0.10 ** p<0.05 *** p<0.01.

Table 2.8: Robustness Tests - Total protein intake

	Protein (mg)													
	Panel A : Full sample							Panel B: BPL households only						
PDS Subsidy value	90.461***	90.461***	98.372***	98.717***	98.713***	124.241***	130.531***	105.472***	105.472***	134.594***	138.520***	138.433***	159.557***	125.667***
	(13.127)	(11.285)	(14.916)	(15.457)	(15.459)	(15.880)	(21.286)	(21.372)	(26.302)	(28.777)	(28.129)	(28.130)	(29.711)	(29.898)
Lead Subsidy value							6.623							2.727
							(8.242)							(9.837)
HH FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SE clustered at State-level		X							X					
State-month FE			X							X				
Village-month FE				X	X	X					X	X	X	
State trends					X							X		
HH trends						X	X						X	
Observations	69846	69846	69846	69846	69846	69846	54857	34233	34233	34233	34233	34233	34233	26718

* p<0.10 ** p<0.05 *** p<0.01.

Table 2.9: Robustness Tests - Total fat intake

	Fat (mg)													
	Panel A : Full sample							Panel B : BPL households only						
PDS Subsidy value	53.594***	53.594***	62.314***	61.349***	61.364***	100.181***	94.943***	61.610***	61.610**	88.556***	96.608***	96.407***	118.320***	91.934***
	(15.078)	(12.809)	(14.903)	(14.608)	(14.588)	(17.644)	(19.110)	(21.474)	(24.000)	(24.312)	(25.145)	(25.140)	(32.921)	(27.088)
Lead Subsidy value							-6.215							-5.998
							(11.592)							(14.821)
HH FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
SE clustered at State-level		X							X					
State-month FE			X							X				
Village-month FE				X	X	X					X	X	X	
State trends					X							X		
HH trends						X	X						X	
Observations	69846	69846	69846	69846	69846	69846	54857	34233	34233	34233	34233	34233	34233	26718

* p<0.10 ** p<0.05 *** p<0.01.

Table 2.10: Isolating the source of variation

	Energy (Kcal)				Protein (mg)				Fat (mg)			
	Base specification	Nominal Subsidy Value	Fix market price to pre-2013 state average	Fix HH-size and composition to pre-2013	Base specification	Nominal Subsidy Value	Fix market price to pre-2013 state average	Fix HH-size and composition to pre-2013	Base specification	Nominal Subsidy Value	Fix market price to pre-2013 state average	Fix HH-size and composition to pre-2013
PDS Subsidy value	4.488***	3.283***	3.895***	3.931***	109.343***	80.318***	95.400***	96.328***	85.646***	58.291***	68.993***	65.555***
	(0.605)	(0.436)	(0.512)	(0.807)	(15.802)	(11.799)	(13.849)	(22.829)	(17.725)	(12.130)	(14.061)	(18.141)
HH FE	X	X	X	X	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X	X	X	X	X	X	X	X
HH-trend	X	X	X	X	X	X	X	X	X	X	X	X
Observations	69846	69846	69846	69846	69846	69846	69846	69846	69846	69846	69846	69846

Table 2.11: Effect of PDS Subsidy expansions on other government benefits (N=69846)

	Middaymeals	NREGA wages income	Pensions	Scholarships and Relief
PDS Subsidy	0.002	0.016	0.015	-0.028
	(0.008)	(0.051)	(0.059)	(0.049)

Standard errors in parentheses are clustered at the village level. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor variable and column heading as the outcome variable. All variables are measured in 2010 rupees.

Table 2.12: Robustness tests after contolling for state-level NREGA policy changes

		NREGA controls interacted with ration card status			
		Budget allocations on NREGA (millions of Rs.)		Implementation of NREGA (in lacs)	
	Base specification (no NREGA controls)	Expenditures	Funds released by Center to State	Number of HHs provided employment	Person days
Energy (Kcal)	3.665***	4.283***	4.267***	4.334***	4.322***
	(0.462)	(0.540)	(0.539)	(0.554)	(0.552)
Protein (mg)	90.461***	105.749***	105.212***	106.984***	106.695***
	(13.127)	(15.253)	(15.230)	(15.802)	(15.661)
Fat (mg)	53.594***	67.465***	66.717***	69.140***	69.072***
	(15.078)	(16.258)	(16.234)	(16.481)	(16.509)
HH FE	X	X	X	X	X
Month FE	X	X	X	X	X
Observations	69846	69846	69846	69846	69846

Standard errors in parentheses are clustered at village level. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with row headings representing outcome variables and PDS subsidy value as the regressor variable and column headings representing the state-level NREGA controls interacted with ration card-status. Data on NREGA budget allocation and implementation comes from Ministry of Rural Development, Government of India and the Statistical year book, published by the Ministry of Statistics and Program Implementation.

Table 2.13: Household resource allocation decisions by gender

	Frequency tabulations (in percentages)		
	Male only	Both	Female only
Assets			
Land	45	49	6
Credit	47	47	6
Livestock	32	59	8
Inputs			
Labor	22	65	13
Fertiliser	57	39	3
Outputs			
Production	39	58	4
Sale Quantity	40	55	5
Fodder	36	60	4
Others			
HH maintenance	13	59	27
Child's education	22	71	7
Migration	41	52	6

Table 2.14: Intra-household bargaining as a facilitator of nutrition through PDS (N=34941)

	Panel A Household Maintainence			**Panel B** Crop production, sale and use			**Panel C** Credit management		
	PDS Subsidy	IH Bargaining	Interaction	PDS Subsidy	IH Bargaining	Interaction	PDS Subsidy	IH Bargaining	Interaction
Nutrient intake									
Total Calorie intake (in kcals)	3.840***	-58.250*	0.473*	4.368***	-66.076**	0.751***	3.892***	25.219	0.179
	(0.595)	(34.527)	(0.275)	(0.763)	(31.835)	(0.279)	(0.655)	(37.406)	(0.360)
Total Protein intake (in milli gms)	95.313***	-1579.460*	11.280	108.957***	-2042.303**	19.561**	97.801***	380.026	4.864
	(15.081)	(905.332)	(7.314)	(19.720)	(899.156)	(7.648)	(16.603)	(1056.374)	(10.132)
Total Fat intake (in milli gms)	58.633***	-922.014	9.440	70.022***	-1718.503*	14.847*	56.932***	1031.574	-5.516
	(15.512)	(835.111)	(6.358)	(18.841)	(900.366)	(8.021)	(16.733)	(917.194)	(8.424)
Expenditures									
Food expenditures total	0.781***	-24.737**	0.161*	0.897***	-16.332	0.171	0.820***	6.238	0.050
	(0.200)	(11.860)	(0.093)	(0.250)	(14.832)	(0.115)	(0.213)	(14.326)	(0.128)
Spending on non-essentials									
Cell and land line phone bill	0.025*	3.459**	-0.028***	0.031	-1.069	0.002	0.035**	-2.518	0.015
	(0.015)	(1.439)	(0.011)	(0.019)	(2.226)	(0.015)	(0.016)	(1.809)	(0.013)
Drugs expenditure (Alcohol, Tobacco)	0.029	1.172	-0.064**	-0.047	2.429	-0.026	-0.002	1.488	-0.019
	(0.047)	(2.820)	(0.025)	(0.061)	(4.656)	(0.037)	(0.056)	(4.161)	(0.036)
Spending on essentials									
Energy expenditure (Charcoal, Kerosene)	0.022***	-0.453	0.011**	0.020***	-0.343	-0.003	0.012**	-0.303	-0.002
	(0.006)	(0.489)	(0.005)	(0.007)	(0.521)	(0.005)	(0.005)	(0.437)	(0.004)
Medical domestic & hospital expenditure	0.328	6.057	-0.094	0.279	3.172	0.011	0.309	-5.103	-0.024
	(0.313)	(28.788)	(0.190)	(0.324)	(25.545)	(0.165)	(0.301)	(31.981)	(0.174)
Education (Fees, books)	-0.051**	-8.269	0.035	0.017	-17.423**	0.127***	-0.027	-10.003*	0.079**
	(0.024)	(5.773)	(0.031)	(0.038)	(6.820)	(0.041)	(0.028)	(5.527)	(0.033)

Standard errors in parentheses are clustered at the village level. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with row headings representing regressor variables and column heading representing dependent variables.

CHAPTER 3

RISK SHARING AND HETEROGENEITY

3.1 Introduction

People in village economies face a large number of income shocks such as drought, floods, crop or business failure, unemployment, sickness, prices fluctuate, etc. Households who fail to insure themselves against such income shocks may experience consumption fluctuations with detrimental effects on household welfare (Gertler and Gruber, 2002; De Weerdt and Dercon, 2006). The protection of households from such income shocks depends on the availability and effectiveness of the existing risk bearing institutions. Storage, accumulation of assets and diversification of crops may be some of the ex-ante means of reducing risk. There may also be ex-post means of coping with risk through informal mutual agreements. That is, households within a village may share risk by pooling their income, as it were, into a common village pot to eliminate their individual income risk. Such informal pooling of risk may potentially provide complete insurance against income shocks (Diamond, 1967; Wilson, 1968). Thus, in order to fully assess the vulnerabilities of households in village economies, where formal credit markets are incomplete or non-existent, it is important for policymakers to understand how well risk sharing groups provide consumption insurance in village economies.

Many households in developing countries are engaged in inter-household insurance arrangements involving state-contingent transfers, as documented by Scott (1977), (Platteau, 1995, 1997), Udry (1990) and others. However, households are generally not completely insured-income and consumption are typically found to be positively correlated. Rejection of full insurance is documented by Rosenzweig (1988), Townsend (1994), Townsend (1995), Udry (1994) and others. Several explanations have been proposed for the failure of full insurance, including moral hazard, limited commitment and hidden income Kinnan (2017). An emerging strand of literature suggests that ignoring heterogeneity in preferences may explain rejections of full risk sharing(Schulhofer-Wohl, 2011; Mazzocco and Saini, 2012; Chiappori et al., 2014).

This study examines whether households share risk efficiently with other households in a village, using ICRISAT's new wave of village data from 2010-2015. In this paper, we derive an alternative method to estimate preferences of households using a full-risk sharing model. Our method of estimating risk-preferences is based on the intuition that a pareto-efficient allocation puts more risk on those who are more risk tolerant, so a household whose consumption strongly co-moves with village consumption must be relatively more risk tolerant.

Our results show that there is substantial and significant heterogeneity in estimated risk preferences. Further, we find that estimated risk tolerance is significantly correlated with wealth and household's characteristics such as number of adult males, household head's education and gender. Households with more migrants are associated with a lower pareto weight in the village-risk sharing, consistent with migrant income as a substitute to informal village risk sharing. Next, we incorporate the estimated risk preferences and test for full risk sharing allowing for this heterogeneity. We reject the null of full risk sharing, irrespective of whether we allow for heterogeneity.

In this paper, we propose a methodological contribution of accounting for heterogeneity in risk sharing tests. Our goal is not to identify the specific mechanisms that support risk sharing or make causal interpretations of the determinants of risk sharing, but we conjecture that risk sharing may include transfers and gifts between households as well as pre-cautionary savings within households. This paper contributes to the new strand of literature on tests of full risk sharing with heterogeneous preferences (Schulhofer-Wohl, 2011; Mazzocco and Saini, 2012; Chiappori et al., 2014). The novelty in our method is that we use a more straighforward method to estimate risk preferences in a simple linear regression. The testing methods developed by Schulhofer-Wohl (2011) and Mazzocco and Saini (2012) require complex non-parametric techniques or large number of households.

This paper proceeds as follows. In Section 2, we review studies that derive tests for risk sharing with the inclusion of heterogeneous preferences and bring to light the most important theoretical assumption of aggregate risk sharing based on preferences. We provide a critique of this new strand of risk sharing literature and contend that there may frictions that may limit households in village economies to share aggregate risk based on preferences; a more clear description of the institutional framework that facilitates sharing of aggregate shocks in village economies seems necessary. This study raises new questions on the motives for sharing risk under aggregate shocks in the hope to improve the theory and construct new models that incorporate salient features of village economies. In Section 3, we derive the standard full risk sharing model and modify the omnibus specification to allow for heterogeneous preferences. In particular, we first derive an alternative method to estimate risk preferences and also present a simple test for bias due to heterogeneous preferences. Next, we test for full risk sharing that allows for heterogeneity, by incorporating the risk and time preference estimates. Finally, we examine the relationship of the estimated parameters with demographic characteristics of the household. In Section 4, we describe the Indian village data. Section 5 presents the empirical results.

3.2 Literature Review

The literature on risk sharing begins with Diamond (1967) and Wilson (1968), who laid the theoretical underpinnings for Pareto optimal risk sharing under uncertainty. Diamond presents a general equilibrium model with uncertainty and shows that consumers (or firms trading in the stock market) are able to raise their expected utility levels, by dividing up claims equally before production (assuming that the stock market permits sharing of risk) and by means of trading among persons of differing degrees of risk aversion. In addition, this firm behavior results in a competitive economy achieving a constrained Pareto optimum. Similarly, Wilson provides an analysis of the decision process of a syndicate - a group of individual decision makers who make a common decision under uncertainty - when the members have diverse risk tolerances. This group decision problem is based on a sharing rule and the criterion for choosing a sharing rule is that it must be Pareto Optimal. The author proves that the syndicate risk tolerance is the sum of the members' risk tolerances. This means that a compensating risk premium for an infinitesimal risk is distributed among the members in proportion to the variance each undertakes to absorb. Thus, a member's incremental sharing proportion is given by his proportion of the syndicate risk tolerance. In summary, the hypothesis for efficient risk sharing - that a Pareto optimal allocation under uncertainty depends only on aggregate risk and not on idiosyncratic risk, with more risk-tolerant members bearing a larger share of the aggregate risk - follows from Diamond (1967) and Wilson (1968)'s work.

A number of studies have empirically tested for efficient risk sharing in different settings. All studies unanimously reject efficient risk sharing using data from developed countries (Cochrane, 1991; Mace, 1991; Attanasio and Davis, 1996; Hayashi et al., 1996; Blundell et al., 2008) and developing countries (Deaton, 1990; Townsend, 1994; Ravallion and Chaudhuri, 1997; Dercon and Krishnan, 2000; Ogaki and Zhang, 2001). For instance, Mace (1991) uses Consumer Expenditure Survey(CES) US data for 1980-83 and rejects full insurance for food consumption. Attanasio and Davis (1996) reject between-group consumption insurance among birth cohorts and education groups in US during the 1980s. Hayashi et al. (1996) use Panel Study of Income Dynamics and reject risk sharing across and within American families.

Townsend (1994)'s seminal paper, one of the first to test for efficient risk sharing in the context of village economies, rejects full insurance at the village level. Similarly, results from nuclear households from Ethiopia (Dercon and Krishnan, 2000), Thailand (Townsend, 1995) and Cote d'Ivoire (Deaton, 1990) suggest the failure of complete intra-village consumption insurance. Hence, a consensus emerged from this research on risk sharing in village economies, which is that, full risk sharing is not taking place at the village level.

Several explanations have been proposed for the failure of full insurance. One is moral hazard, that one households actions are not observable to others, so shirking is possible (Rogerson, 1985; Golosov et al., 2003). Another is limited commitment, that households receiving high income draws may leave the insurance arrangement instead of contributing to the insurance pool (Kimball, 1988; Coate and Ravallion, 1993; Ligon et al., 2002; Laczó, 2015). A third possibility is hidden income, that households income realizations are unobservable, so that it is possible to claim lower income (Townsend, 1982). Kinnan (2017) cleanly documents all the three possibilities and supports the predictions of hidden income, but rejects limited commitment and moral hazard using panel data from rural Thailand. A fourth possibility is that, villages may not be an appropriate unit of pooling risk in village economies and risk sharing may take place within subgroups in a village (Ellsworth, 1988; Platteau, 1997; Fafchamps and Lund, 2003; Goldstein et al., 2005; De Weerdt and Dercon, 2006); factors such as size and social characteristics of risk sharing groups may be important aspects in determining the amount of risk-sharing that occurs.

An emerging strand of literature suggests that ignoring heterogeneity in preferences may explain rejections of full risk sharing. Schulhofer-Wohl (2011) and Mazzocco and Saini (2012) show that standard risk sharing tests may spuriously reject full insurance, as they assume homogeneous preferences. If households have heterogeneous preferences, then those with more risk tolerance would bear more aggregate risk. As a result, the income coefficient in the full insurance test specification would be biased upwards and may lead to spurious rejections of full insurance.

3.2.1 Risk sharing with heterogeneous preferences

The literature on risk sharing tests with heterogeneous preferences is nascent and mainly comprises three prominent studies by Schulhofer-Wohl (2011), Mazzocco and Saini (2012) and Chiappori et al. (2014); each study proposes a different testing approach. Schulhofer-Wohl (2011) and Chiappori et al. (2014) conduct a parametric test by estimating the benchmark risk sharing specification derived from the first order condition that household consumption depends only on aggregate shocks and not on idiosyncratic shocks. Schulhofer-Wohl (2011) first provides empirical evidence consistent with the hypothesis that incomes are more strongly correlated with aggregate shocks for more risk tolerant agents. Using panel data from Health and Retirement Survey from 1923-47, the author shows that risk tolerant workers hold jobs in which earnings carry more aggregate risk. In deriving the econometric methods to test for full risk sharing, Schulhofer-Wohl (2011) treats risk preferences as nuisance parameters that must be eliminated from the full risk sharing equation. The author uses quasi-fixed effects that controls for household specific trends and household specific effects of aggregate shocks, thereby removing any heterogeneity in preferences.

While Schulhofer-Wohl (2011) avoids estimating preferences, Chiappori et al. (2014) measure each households preferences upto a scale by examining how much its consumption co-moves with aggregate consumption. The intuition is that, if two householdss consumptions are strongly correlated, they must both have consumption that moves strongly with aggregate shocks; they must both be relatively risk tolerant. Similarly, if two householdss consumption is not strongly correlated, atleast one must have consumption that does not move strongly with aggregate shocks; at least one must be risk verse. The authors use this intuition to impute risk preferences of each household by considering their pair-wise correlation of consumption. The estimated risk preferences for each household are then substituted in the omnibus full insurance specification to control for preference heterogeneity.

Mazzocco and Saini (2012), on the other hand, use a non-parametric test that allows for a general class of utility functions. Efficient risk sharing is tested for household pairs. Instead of relying on the first order conditions, the authors use a household risk sharing function which is basically household expenditure as a function of aggregate resources (sum of expenditures for the household pair). The efficiency test for a household pair comprises of whether a households expenditure is monotonically increasing with the sum of expenditures for the pair. The test is repeated for all the possible household pairs in a group and the hypothesis of full risk sharing for the group is rejected if one of the pairs in the group fails to share risk efficiently. The use of risk sharing functions incorporates heterogeneity in risk preferences and non-separability between consumption and leisure.

Actually, Townsend (1994) in part tests for full insurance that allows for heterogeneous preferences. Townsend runs separate time-series regressions for each household and tests whether the coefficient on the idiosyncratic income is equal to zero and if the aggregate consumption (or the village leave-out mean) is equal to one for each household. Kurosaki (2001) follows a similar procedure, using the same ICRISAT data, and estimates household by household regression with the inclusion of a time trend to account for heterogeneity in time preferences. But the power of these tests is very weak, given the short time dimension of panel data on consumption, only 10 periods for each household in a village. Furthermore, Dubois (2001) tests for full insurance allowing risk aversion to vary with observed household characteristics, but rules out unobserved heterogeneity.

3.2.2 Critique of the literature

The basic premise for including heterogeneous preferences in testing for efficiency is that omitted variable bias in standard tests under homogeneous preferences drives the income coefficient upwards, leading to spurious rejections of full insurance (Schulhofer-Wohl, 2011; Mazzocco and Saini, 2012). The motivation to include heterogeneous preferences, more than controlling for the econometric bias, points toward accounting for the theoretical implication of aggregate risk sharing based on preferences which has been ignored in the literature. Mazzocco and Saini (2012) explain risk sharing as a two-step process, characterized by two types of shocks idiosyncratic and aggregate. The first step involves idiosyncratic risk sharing wherein households pool their individual resources and hence eliminate the idiosyncratic risk they face. The second step consists of aggregate risk sharing wherein households with heterogeneous preferences insure each other against aggregate risk by allocating pooled resources according to their individual preferences; more risk tolerant households bear a larger share of aggregate risk. The need to account for heterogeneous preferences stems from the second step, which is mostly ignored in the literature.

In theory, a Pareto-efficient consumption allocation puts more aggregate consumption risk on those who are less risk averse. This theoretical implication holds true under complete markets, supported by an institutional structure with a complete set of state contingent claims (or Arrow-Debreu securities) and infinite agents who can trade these securities to hedge against aggregate risk (Diamond, 1967; Wilson, 1968). However, village economies are characterized by incomplete markets with frictions and a lack of institutional framework to facilitate sharing of aggregate risk. It is important to examine the motive for risk sharing for aggregate shocks; whether there are informal enforcement mechanisms that create incentives for households with different risk preferences to share aggregate risk, keeping in mind the features of village economies. Households in a village may have different risk preferences. But, the presence of heterogeneous risk preferences may not directly translate to sharing of aggregate shocks based on preferences.

It may be probable for a risk neutral agent in a village - e.g., a bank or a rich individual - to insure risk averse individuals subject to aggregate shocks. This kind of protection against aggregate shocks that a rich individual provides to poorer individuals, often called as patron-client relationships, is explored in the sociological and anthropological literature (Scott, 1977; Platteau, 1995). But, such arrangements have practically disappeared from village economies (Bardhan and Rudra, 1980) and is reported to be absent in ICRISAT villages (Walker and Ryan, 1990).

Contrary to the assumption that aggregate shocks is a significant component of efficient risk sharing in village economies, several studies indicate that risk sharing breaks down under aggregate shocks, especially for poor households, since everyone is affected (Ray, 1998; Dercon, 2005; Pan, 2009; Gunther and Harttgen, 2009; Bhattamishra and Barrett, 2010; Binswanger-Mkize, 2013). For instance, Rosenzweig and Binswanger (1993) use the same ICRISAT data and find that food consumption declines with village level weather shocks but not for idiosyncratic shocks such as illness or accidents, suggesting that informal mechanisms may not insure aggregate risk. Pan (2009) indicate that inter-household transfers from informal risk sharing networks can only insure idiosyncratic but not covariate shocks in rural Ethiopian villages. Reardon et al. (1988) find that intra-village transfers accounted for only two and one percent of losses suffered by the poorest households in the Sahalian and Sudanian villages of Burkina Faso, after a drought in 1987. Similarly, Kazianga and Udry (2006) use village panel data in Burkina Faso and report that transfers during drought between 1981 to 1985 were too small to play any significant role in consumption smoothing. Shoji (2008) uses a panel dataset of 126 villages in Bangladesh and shows that quasi-credit within villages was not available during severe floods in 1998.

And even if one accounts for sharing of aggregate risk, there is little scope to share the aggregate component of income risk as the idiosyncratic component of income risk is more dominant in village economies (Udry, 1990; Townsend, 1995; Deaton, 1997; Lybbert et al., 2004; Morduch, 2005; Gunther and Harttgen, 2009). For instance, Morduch (2005) uses the same ICRISAT village data and reports that idiosyncratic risk (inclusive of measurement error) accounts for 75-96% of the total variance in income within these villages. Similar magnitudes are reported using data from Nigeria (Udry, 1990), Thailand (Townsend, 1995) and Cote d'Ivoire (Deaton, 1997).

Furthermore, while methods that account for heterogeneous preferences correct for econometric bias, it is important to understand the need to account for heterogeneous preferences and assess the relative significance of correcting the bias. Does the implication of full risk sharing (or a failure) under homogeneous preferences substantially differ after correcting for the bias due to heterogeneous preferences? Shrinivas and Fafchamps (2018) show that the standard tests do not yield results that are markedly different from those provided by the heterogeneity-robust tests in Mazzocco and Saini (2012). Chiappori et al. (2014) note that the hypothesis of full risk sharing is not rejected for Thai village data under homogeneous and heterogeneous preferences. Schulhofer-Wohl (2011) derives econometric tests of full insurance that account for both time and risk preferences using two methods - factor models and GMM; wherein GMM further allows non-separability between consumption and leisure. Using PSID data, Schulhofer-Wohl (2011) rejects full insurance for both homogeneous and heterogeneous cases from the factor method estimates and from GMM (for risk preferences only) under the assumption of separability. Allowing for non-separability and time preferences reduces the coefficient on income, more so for time preferences which reduces the income coefficient to a negative value and statistically indistinguishable from zero. As a result, insurance is not rejected, under the case when both time preferences and non-separability are allowed. Also in Townsend (1994), empirical results from the time-series regressions are largely similar to the pooled-panel regressions, that a significant degree of idiosyncratic shocks are smoothed.

In summary, a major implication from the three major studies that test for risk sharing with heterogeneous preferences is that the results for tests under homogeneous preferences are largely similar with those that allow heterogeneous preferences. Moreover, there is convincing evidence that risk sharing breaks down under aggregate shocks and there is little scope to share aggregate shocks in village economies. Hence, before employing new risk sharing tests with heterogeneous risk preferences, a motivation for heterogeneity in terms of policy implications and a more clear description of the institutional framework that supports sharing of aggregate shocks in village economies seems necessary.

3.3 Theory

In this section, we derive the standard full insurance specification, based on Diamond (1967) and Wilson (1968) and modify the omnibus specification to allow for heterogeneous risk and time preferences.

Assume a closed exchange economy. Imagine a village with N households each with variable income y_{jt} that depends on the state of nature s. Suppose that s represents a complete depiction of the state of nature - i.e. for individual j in household i as well as all other $N-1$ households in the village. Let consumption of individual j at time period t be denoted as c_{jt}, consumption of household i be denoted as c_{it} and suppose consumption and leisure are separable. Individuals live infinitely and discount the future with common discount factor ρ. Inter-temporal expected utility of individual j is written as:

$$EU = \sum_{t=0}^{\infty} \rho^t \sum_{r=1}^{S} Prob(s_{rt}) U_j \left[c_{jt}(s_{rt})\right] \tag{3.1}$$

where $Prob(s_{rt})$ denotes the probability of state of the world s_r at time t. The set of Pareto optimal consumption allocations is found by maximizing the social planner problem for all possible welfare weights η_j:

$$\max_{c_{it}(s_{rt})} \sum_j \eta_j \sum_{t=0}^{\infty} \rho^t \sum_{r=1}^{S} Prob(s_{rt}) U_j \left[c_{jt}(s_{rt})\right] \qquad \text{subject to} \tag{3.2}$$

$$\sum_j c_{jt}(s_{rt}) = \sum_j y_{jt}(s_{rt}) \qquad \text{(feasability constraint)} \tag{3.3}$$

where, $\sum_{j=1}^{N} \eta_j = 1$. Let the Lagrange multiplier associated with each feasibility constraint be denoted as $\lambda(s_{rt})$. First- order conditions are

$$\eta_j \rho_j^t U_j^{'}(c_{jt}(s_{rt})) - \lambda(s_{rt}) = 0 \tag{3.4}$$

where, η_j is the Pareto weight of individual j which remains unchanged over time, and $\lambda(s_{rt})$ is the same for all households in each state of the world. $\lambda(s_{rt})$ can also be interpreted as a measure of the aggregate resource constraint faced by all N households in the village in period t. To simplify the notation, suppose the dependence of s is suppressed :

$$\eta_j \rho_j^t U^{'}(c_{jt}) = \lambda_t \tag{3.5}$$

The most important implication of the above first-order condition is that, individual consumption c_{jt} is contingent on λ_t. Now, since the Lagrange multiplier λ_t depends on aggregate income $\sum_j y_{jt}$ or aggregate consumption $\sum_j c_{jt}$, it follows that, under efficient risk sharing, individual consumption c_{jt} varies only with aggregate consumption. In other words, conditional on aggregate consumption, idiosyncratic variables such as individual income y_{jt} do not affect consumption at all. In contrast, under autarky or no risk-sharing, individual consumption c_{jt} would closely track individual income y_{jt}. This is the basis for the exclusion restriction test of risk sharing efficiency.

In order to construct a formal statistical test and bring the above implication to data, assume an exponential functional form for the utility function:

$$U(c_{jt}) = \left[\frac{-1}{\gamma_i}\right] \exp[-\gamma_i c_{jt}]$$

where γ_i is the coefficient of risk aversion of household i. Substituting the first differential of the above equation in equation 3.5, we get:

$$\begin{aligned} \eta_j \rho_j^t \exp[-\gamma_i c^*_{jt}] &= \lambda_t \\ \log \eta_j + t \log \rho_j - \gamma_i c^*_{jt} &= \log \lambda_t \\ c^*_{jt} &= \frac{\log \eta_j}{\gamma_i} + t\frac{\log \rho_j}{\gamma_i} + \frac{1}{\gamma_i}(-\log \lambda_t) \end{aligned}$$

Now, suppose we assign common weights η_j to all individuals j in household i, we get the standard full insurance specification at the household level as:

$$c^*_{it} = \frac{\log \eta_i}{\gamma_i} + t\frac{\log \rho_i}{\gamma_i} + \frac{1}{\gamma_i}(-\log \lambda_t) \tag{3.6}$$

Equation (3.6) says that aggregate shocks λ_t have a larger effect on households that have smaller co-efficients of risk aversion γ_i and that consumption rises faster for households with larger rates of time preferences ρ_i or larger elasticities of intertemporal substitution $1/\gamma_i$. However, estimation of equation (3.6) to test the full-risk sharing implicaiton is non-trivial as the aggregate resource constraint $log \lambda_t$ is unobservable. Under the null of full risk sharing equation (3.6) holds for all the households in the village $(i = 1, 2...N)$. Therefore, one simple solution is to aggregate equation (3.6) for all the households in the village:

$$\sum_{i=1}^{N} c_{it} = \sum_{i=1}^{N} \frac{\log \eta_i}{\gamma_i} + \sum_{i=1}^{N} t \frac{\log \rho_i}{\gamma_i} + \sum_{i=1}^{N} \frac{1}{\gamma_i}(-\log \lambda_t)$$

$$\frac{1}{N}\sum_{i=1}^{N} c_{it} = \frac{1}{N}\sum_{i=1}^{N} \frac{\log \eta_i}{\gamma_i} + t\frac{1}{N}\sum_{i=1}^{N} \frac{\log \rho_i}{\gamma_i} + (-\log \lambda_t)\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}$$

$$\frac{\frac{1}{N}\sum_{i=1}^{N} c_{it}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}} = \frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \eta_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}} + t\frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \rho_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}} + (-\log \lambda_t)$$

Substituting for $(-\log \lambda_t)$ from (3.6) and define $\frac{1}{N}\sum_{i=1}^{N} c_{it} = \overline{c_t}$ as the average village consumption and consumption is measured with an additive error: $c^*_{it} = c_{it} + \epsilon_{it}$, we have

$$\frac{\overline{c_t}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}} = \frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \eta_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}} + t\frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \rho_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}} + [\gamma_i c_{it} - \log \eta_i - t \log \rho_i] + \epsilon_{it}$$

$$\gamma_i c_{it} = \frac{\overline{c_t}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}} + \left[\log \eta_i - \frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \eta_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}}\right] + \left[\log \rho_i - \frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \rho_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}}\right] t + \epsilon_{it}$$

$$c_{it} = \left(\frac{\frac{1}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}}\right)\overline{c_t} + \frac{1}{\gamma_i}\left[\log \eta_i - \frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \eta_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}}\right]$$

$$+ \frac{1}{\gamma_i}\left[\log \rho_i - \frac{\frac{1}{N}\sum_{i=1}^{N} \frac{\log \rho_i}{\gamma_i}}{\frac{1}{N}\sum_{i=1}^{N} \frac{1}{\gamma_i}}\right] t + \epsilon_{it} \qquad (3.7)$$

A reduced form of the above equation gives the standard full risk sharing specification:

$$c_{it} = \alpha_i + \beta_i \overline{c_t} + \theta_i t \tag{3.8}$$

Equation (3.8) says that a pareto-optimal consumption allocation, under the null of full risk sharing, depends only on aggregate shocks and not idiosyncratic shocks. In other words, any idiosyncratic variables such as household income y_{it} do not enter equation (3.8), once aggregate shocks $\overline{c_t}$ are controlled. Hence, by adding household income y_{it} into (3.8), we get:

$$c_{it} = \mu_i + \beta_i \overline{c_t} + \theta_i t + \xi_{it} y_{it} \tag{3.9}$$

The test for efficient risk sharing constitutes testing the hypothesis that $\xi_{it} = 0$.

3.3.1 Heterogeneity bias in risk-sharing tests

Most studies on efficient risk sharing do not estimate (3.7). Rather, a common co-efficient of risk aversion $\gamma_i = \gamma$ and a common discont factor $\rho_i = \rho$ i.e homogeneous risk and time preferences for all households in the village are assumed and the following is estimated:

$$c_{it} = \frac{1}{\gamma} \ \overline{c_t} + \frac{1}{\gamma}\left(\log \eta_i - \frac{1}{N}\Sigma_j \log \eta_j\right) + \xi_{it} y_{it} + \epsilon_{it}^{equal} \tag{3.10}$$

which is much simpler than equation (3.7) because the first and second terms in the R.H.S of equation (3.10) are just time and household dummies. Cochrane (1991), Mace (1991) and Townsend (1994) assume homogeneous preferences and test for efficient risk sharing using a specification similar to equation (3.10).

The basic point of including heterogeneous preferences is that omitted variable bias drives the income coefficient in (3.10) upwards leading to spurious rejections (Schulhofer-Wohl, 2011; Mazzocco and Saini, 2012). If the true model is (3.7) but a researcher mistakenly estimates (3.10), the error term in (3.10) is :

$$\epsilon_{it}^{equal} = \left(\frac{1}{\gamma_i} - \frac{1}{\gamma}\right) \overline{c_t} + \epsilon_{it}$$

The least-square estimate ξ in equation (3.10) is unbiased if $Cov(y_{it}, \epsilon_{it}^{equal}) = 0$, and biased upwards if $Cov(y_{it}, \epsilon_{it}^{equal}) > 0$. Suppose household income is decomposed into aggregate and idiosyncratic components, that is, let $y_{it} = e_i a_t + u_{it}$ where a_t is the common shock, e_i elasticity of household i to the common shock and u_{it} is the idiosyncratic shock. Assuming that e_i is stationary and u_{it} and ϵ_{it} are $i.i.d$, then,

$$\begin{aligned} Cov(y_{it}, \epsilon_{it}^{equal}) &= Cov\left[e_i a_t, \left(\frac{1}{\gamma_i} - \frac{1}{\gamma}\right)\overline{c_t}\right] \\ &= Cov(a_t, \overline{c_t})\ \ Cov(e_i, \frac{1}{\gamma_i}) \end{aligned} \tag{3.11}$$

Aggregate shock a_t and aggregate consumption $\overline{c_t}$ are most likely to be positively correlated, that is $Cov(a_t, \overline{c_t}) > 0$. Hence, $Cov(y_{it}, \epsilon_{it}^{equal}) > 0$ if $Cov(e_i, \frac{1}{\gamma_i}) > 0$. That is, income coefficient in (3.11) is biased upwards if the elasticity of income to aggregate shocks is greater for less risk averse households. Similarly, it can be shown that income coefficient would be biased upward if households have heterogeneous time preferences. These results are formally proved in Proposition 1 in Mazzocco and Saini (2012).

3.3.2 Estimation of risk and time preferences and pareto weights

In this section, we derive an alternative method to estimate risk preferences, time preferences and pareto weights of households, identified upto a scale, using the full risk sharing model. It is important to note that our method is valid under the maintained assumption that households share risk efficiently in the village.

First, we normalize risk preferences upto a village-specific scale.[1] In other words, let the village average risk tolerance be equal to one ($\frac{1}{N}\sum_{i=1}^{N}\frac{1}{\gamma_i} = 1$), then the full-risk sharing specification in (3.7) reduces to :

[1] Chiappori et al. (2014) also assume a mean risk tolerance equal to unity and identify risk preferences upto a scale. The intution is based on Wilson (1968), that doubling every household's coefficient of risk aversion will not change the set of Pareto-efficient allocations.

$$
\begin{aligned}
c_{it} &= \left(\frac{1}{\gamma_i}\right)\overline{c_t} + \frac{1}{\gamma_i}\left[\log \eta_i - \frac{1}{N}\sum_{i=1}^{N}\frac{\log \eta_i}{\gamma_i}\right] \\
&\quad + \frac{1}{\gamma_i}\left[\log \rho_i - \frac{1}{N}\sum_{i=1}^{N}\frac{\log \rho_i}{\gamma_i}\right] t + \epsilon_{it} \\
c_{it} &= \beta_i \overline{c_t} + \alpha_i + \theta_i t \qquad (3.12)
\end{aligned}
$$

Where:

$$\beta_i = \frac{1}{\gamma_i} \qquad (3.12A)$$

$$\alpha_i = \frac{1}{\gamma_i}\left[\log \eta_i - \frac{1}{N}\sum_{i=1}^{N}\frac{\log \eta_i}{\gamma_i}\right] \equiv \beta_i\left[\log \eta_i - \frac{1}{N}\sum_{i=1}^{N}\beta_i \log \eta_i\right] \qquad (3.12B)$$

$$\theta_i = \frac{1}{\gamma_i}\left[\log \rho_i - \frac{1}{N}\sum_{i=1}^{N}\frac{\log \rho_i}{\gamma_i}\right] \equiv \beta_i\left[\log \rho_i - \frac{1}{N}\sum_{i=1}^{N}\beta_i \log \rho_i\right] \qquad (3.12C)$$

Under the null of full risk sharing, equation (3.12) is valid for each household i. Hence, household specific coefficients $\hat{\beta}_i$, $\hat{\alpha}_i$ and $\hat{\theta}_i$ can be estimated by employing household-by-household time series regressions, similar to Townsend (1994) and Kurosaki (2001). However, it is important to consider a few caveats in estimating (3.12). First, the dependent variable in (3.12) is measured with errors. We asssume that the errors are independent and identically distributed ($i.i.d$) for a given household, which delivers an $i.i.d$ term in the time-series regression. And, in the right hand side, village average consumption is approximated by the sample average $\overline{c}_t$, by the law of large numbers. However, the sample average is still an approximation. Thus, instead of full mean, we use the sample leave-out mean (village mean without including the household under consideration). In Appendix A, we show that leave-out mean is superior than full mean, especially when there is measurement error. Thus, we substitute the leave-out instead of full-mean, as follows:

$$c_{it} = \beta_i \overline{c}_{-t} + \alpha_i + \theta_i t \qquad (3.13)$$

where $\overline{c}_{-t}$ represents the leave-out village mean consumption. The coefficient on village consumption β_i has a definite interpretation - it represents the risk tolerance of household i. As we have set the village mean risk tolerance equal to unity ($\frac{1}{N}\Sigma\beta_i = 1$), households with $\beta_i > 1$ can be interpreted as more risk tolerant as they bear more aggregate risk or consume more from the average village pool $\bar{c}_{-t}$. Similarly, households with $\beta_i < 1$ can be interpreted as less risk tolerant.

But, unlike β_i, it is difficult to directly interpret the coefficients α_i and θ_i. Using α_i and θ_i, we can however recover household parameters $\log \eta_i$ and $\log \rho_i$, which have a more amenable interpretation - $\log \eta_i$ represents the pareto weight of household i in the risk sharing arrangement and $\log \rho_i$ represents a combination of pure time preferences and life-cycle motives. Equations (3.12B) and (3.12C) can be re-written as,

$$\log \eta_i = \frac{\alpha_i}{\beta_i} + \frac{\overline{\alpha}}{1 - \overline{\beta}} \tag{3.13A}$$

$$\log \rho_i = \frac{\theta_i}{\beta_i} + \frac{\overline{\theta}}{1 - \overline{\beta}} \tag{3.13B}$$

where, $\overline{\alpha}$, $\overline{\beta}$ and $\overline{\theta}$ represent the village average α_i, β_i and θ_i. Appendix C.1 shows the algebra.

The estimation procedure is as follows. First, we obtain household specific coefficients $\hat{\beta}_i$ $\hat{\alpha}_i$ and $\hat{\theta}_i$ by estimating (3.13) for each household and then plugin these estimates in equations (3.13A) and (3.13B) to obtain $\hat{\log} \eta_i$ and $\hat{\log} \rho_i$. Hence, our estimation method is simple and straightforward; by running household-by-household time series regressions, we obtain estimates of household i's risk tolerance $\hat{\beta}_i$, time preference $\hat{\log} \rho_i$ and pareto weight $\hat{\log} \eta_i$, upto a village-specific scale.

3.3.3 Test for heterogeneity bias

Risk tolerance estimates, obtained using our simple method, permits a direct test of the hypothesis that incomes are more correlated with aggregate shocks for more risk tolerant households; that is, whether $Cov(e_i, \frac{1}{\gamma_i}) > 0$ in (3.11). This hypothesis is the central point of allowing for heterogeneous preferences in risk sharing tests. The relationship between household income and aggregate shocks for more risk tolerant vs less risk tolerant households can be examined by employing an interaction model:

$$\Delta y_{it} = \psi_i^1 + \psi_{it}^2 \Delta \bar{c}_{-it} + \psi_{it}^3 (\hat{\beta}_i * \Delta \bar{c}_{-it}) \tag{3.14}$$

where $\hat{\beta}_i$ is the risk tolerance estimate obtained from (**??**). The test for bias due to heterogeneous preferences constitutes whether the coefficient on the interaction term is positive ($\psi_{it}^3 > 0$). In other words, whether the elasticity of income to aggregate shocks e_i in (3.11) is greater for more risk tolerant households. If the hypothesis $\psi_{it}^3 = 0$ is not rejected, then heterogeneous preferences do not bias the standard test of full risk sharing in (3.10). However, if the hypothesis $\psi_{it}^3 = 0$ is rejected and the alternative $\psi_{it}^3 > 0$ is accepted, then it implies that the standard test of full risk sharing may be biased due to heterogeneity in the data. As shown in (3.11), heterogeneity matters only for those risk sharing groups with a positive bias. Once the risk sharing groups with a heterogeneity bias are identified, new risk sharing tests that allow for heterogeneity need to be employed.

3.3.4 Test of risk sharing with heterogeneity

In this section, we derive an alternative method to test for full risk sharing that eliminates the bias from heterogeneous risk and time preferences. It is important to note that our method eliminates the bias derived only from heterogeneous preferences and does not control for any other source of bias.

First, we obtain estimates of risk tolerance $\hat{\beta}_i$ by estimating time series regressions, as in (**??**), for each household. Next, we substitute the risk tolerance estimates in the full risk sharing test (3.12) :

$$\begin{aligned} c_{it} &= \hat{\beta}_i \overline{c_t} + \alpha_i + \theta_i t + \xi_{it} y_{it} \\ c_{it} - \hat{\beta}_i \overline{c_t} &= \alpha_i + \theta_i t + \xi_{it} y_{it} \\ \Delta(c_{it} - \hat{\beta}_i \overline{c_t}) &= \theta_i + \xi_{it} \Delta y_{it} \end{aligned} \tag{3.15}$$

where Δ is the first difference operator and y_{it} is household income. The test of efficient risk sharing constitutes testing the hypothesis that $\xi_{it} = 0$. Note that (3.15) is similar to the pooled-panel regression employed by Townsend

(1994), except that Townsend (1994) assumes homogeneous preferences and sets the coefficient $\hat{\beta}_i = 1$. As $\hat{\beta}_i$ appears only in the dependent variable, we do not need to correct the point estimates or standard errors in (3.15) to account for the estimation of $\hat{\beta}_i$ in the previous step. Furthermore, biased estimates of $\hat{\beta}_i$ do not affect our test as long as the bias is common across all households in the village.

In principle, we can also estimate θ_i and obtain each household's time preferences ρ_i. However, unlike β_i, it is difficult to interpret the coefficients θ_i and ρ_i, as it represents a combination of pure time preferences and life-cycle motives. We can however, remove any heterogeneity in time preferences by double differencing:

$$\Delta^2 \left(c_{it} - \hat{\beta}_i \, \overline{c_t}\right) = \xi_{it} \, \Delta^2 y_{it} \tag{3.16}$$

where Δ^2 is the double difference operator. First difference eliminates the household specific intercept α_i; second difference eliminates household specific discount factos θ_i and any unobserved household specific characteristics that have a constant time trend. Hence, our full risk sharing test specification in (3.16) controls for heterogeneity in both risk and time preferences.

3.4 Data

We use the new wave of ICRISAT's VDSA panel data[2] of 1300 households observed over 60 months from June 2010 to July 2015. The VDSA data cover 30 villages spread across eight states in India with four villages in each state, except Madhya Pradesh which has only two. The states covered are Andhra Pradesh, Bihar, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maha-

[2]ICRISAT's Village level studies (VLS) are longitudinal surveys collected between 1975 to 1985 in six villages in the semi-arid tropics of India. Data collection was restarted from 2001 in the same six villages, tagged as the second generation of VLS (VLS2). However, the frequency of household surveys from 2001 to 2004 was limited to annual observations based on the availability of funds, and was increased to monthly data in 2005-06. It was only after 2009, with the funding from the Gates foundation, the VLS was expanded significantly and was renamed as the Village Dynamics in South Asia (VDSA). In 2009, 12 villages in the semi-arid tropics, in addition to the 6 old VLS villages, and 10 more villages from east India were included; summing to a total of 30 villages across India. The data for panel year 2009, however, has many gaps, especially in the consumption module, and is inconsistent with the subsequent panel years. Accordingly, this paper uses data beginning from panel year 2010 until 2014.

rashtra and Orissa; with 4 villages in each state, except Madhya Pradesh that has only 2 villages.

The VDSA panel data are geographically divided into 18 villages in the Semi-Arid Tropics (SAT) and 12 villages in the Eastern region of India. Similar to the old VLS, households in each village are randomly selected to represent households in four land-holding classes: large, medium, small and landless. The data follows the agricultural cycle in India from June to July. Endowment and household characteristics such as household size and landholding size are collected annually at the beginning of every panel year in June. Monthly data on food and nonfood expenditures, sale of crop and livestock, selling and buying of assets, credit are recorded in the Transactions module.

Total household expenditure is calcuted using Transactions module, defined as sum of expenditures on food and non-food items. Monthly income is calculated from plot cultivation, employment and transactions modules. Income constructed as revenue minus costs; where revenue includes crop and livestock revenue and income from formal and informal credit and cost includes value of inputs for crop cultivations and own labor hours supplied by men, women and children. Consumption and income data are expressed in real values, deflated to 2010 rupees.

3.5 Results

We first present results from estimating household-by-household regressions, as in (3.13). Table 1 reports the summary of results, how the number of rejections of standard risk sharing at the village-level changes for difference model specfcations. Results are not adjusted for multiple hypothesis testing.

In Panel A, we examine whether results are sensitive to the specification of aggregate shock measure/village consumption. For the sake of comparison, the first column shows results when we include time dummies (similar to Ravallion and Chaudhuri (1997)) instead of village consumption. Full mean in column (2) represents the village average of weighted consumptions (what Townsend uses) as against weighted average of household consumptions in column (3). We do not find any signficant difference in the results with full mean vs weighted average. Although, the number of rejections marginally increases with leave-out mean.

In Panel B, we examine whether results are sensitive to whether risk or time preferences, or both are included. Standard test are results from standard test under homogeneous preferences with village leave out mean to control for aggregate shocks (similar to Ravallion and Chaudhuri (1997)). With Risk Pref, is only accounting for risk preferences, that is by substituting the risk tolerance estimate from time series regression. With Time pref, is only controlling for time preference, that is by double differencing. Results show that the number of rejections decreases when both risk and time preferences are included.

In Panel C, we examine the results from household-by-household time series regressions. First, we conduct LR test whether all the household-specific βs (risk tolerance) are equal in a village. This is essentially a test of preference homogeneity. Homogeneity in preferences is rejected signficantly for the majority of villages. Second, we test the implication full risk sharing model, that coefficient on village consumption $\beta = 1$ and coefficient on the income $\xi = 0$. In other words, we test whether the village mean of the estimated $\Sigma\beta_i = 1$. Note that Townsend tests if $\beta = 1$ for each household (and only 10 annual observations for 10 years) and we test if the village mean $\Sigma\beta_i = 1$(Number of HHs range from 28 to 88). If there is heterogeneity, the right way to test the complete markets hypothesis with these time series results is not if $\beta = 1$ for each household, but whether the village average of the estimated $\Sigma\beta_i = 1$. But, this test is weak anyway and measurement errors on consumption would make it unreliable.

In Tables 2 and 3 provide the detailed results. Table 2 reports the average values and standard deviaitions across households of the coeffcient estimates β_i on village leave-out consumption (also interpreted as the village mean of risk tolerances), and ξ_{it} on household income. Risk tolerance estimates range from 0.509 to 1.096 and income cofficients's averages are from 0.007 to 0.315. Null of homogeneous risk preferences (common coefficient of β within villages) is rejected at 5% level for 25 out of 30 villages. The null of full risk sharing, a joint test of $\beta_i = 1 \& \xi_{it} = 0$ is rejected for the full risk sharing hypothesis, for 16 villages at the 5% signficance level and 11 villages at 1% signficance level.

Table 3 compares the results from standard test and heterogeneity robust test. The first column presents results from standard tests under homogeneous preferences. The second column presents the heterogeniety bias test results, as explained in Section 3.3. That is, the coefficient estimate on the interaction term in (3.14). And the third column reports the esimates from heterogeneity robust tests.

Results imply that there is heterogeneity bias in a few villages (9 out of 30). Correction for this bias, does reduce the magnitude of the coefficient on income, especially for the case of risk preferences. The direction of bias for tIme preferences seems erratic.

Overall, the results imply that results from standard test and the heterogeniety robust tests are similar. Hence, these results raise questions on the need to account for heterogeneous preferences and the relative significance of correcting the bias.

3.5.1 Association with Demographics

Table 3.4 shows the relationship between estimated household parameters - risk tolerance $\hat{\beta}_i$, time preference $\hat{\log \rho_i}$ and pareto weight $\hat{\log \eta_i}$ - and observed demographic characteristics of the households at the beginning of the 2010 panel year. Even though the estimates are noisy measures, the results are intuitive and in agreement with earlier studies. We find more statistically significant results on risk tolerance, compared to time preferences and pareto weights. Risk tolerance is negatively associated with number of men and children in the household and positively associated with education and gender of household head and expenditure quintile of the household. These results are consistent with previous studies that show that, in general, higher levels of risk tolerance is associated with higher levels of education, older males, male headed households and wealth. Time preferences are negatively associated with number of children in the household and the expenditure quintile of the household. Lastly, pareto weight is negatively associated with number of members outside in the household. This result is consistent with the implicit risk sharing contracts - households with migrants are given a lower pareto weight in the risk sharing arrangement.

3.6 Conclusion

This paper proposes a methodological contribution of testing for full risk sharing with heterogeneous risk and time preferences. We reject the null of homogeneity in preferences and show that there is substantial heterogeneity in preferences. However, we reject full risk sharing for both cases - with and without heterogeneity. Therefore, risk sharing implications are similar for tests that allow for heterogeneity with tests that assume homogeneity. Our method uses a long panel data from India, treating villages as the risk-sharing unit. Estimated risk and time preferences are associated with wealth and other household characteristics, suggesting an incomplete separation between consumption and production, a characteristic of incomplete markets.

3.7 Figures and Tables

Table 3.1: Summary of risk sharing test results

	Using each test, how often is risk sharing rejected at the 1% level				
	(1)	(2)	(3)	(4)	(5)
Panel A	Month dummies	Full mean	Leave-out	Weighted Average	Wt. Avg Leave out
Weighted Avg and Leave out	13/30	12/30	14/30	11/30	12/30
Panel B	Standard test	With Risk pref	With Time pref.	Risk and Time	
Does Heterogeneity matter?	14/30	11/30	12/30	8/30	
Panel C	Equal βs within vill	Avg vill $\beta = 1$	Avg vill $\xi = 0$	$\beta = 1 \& \xi = 0$	
Tests on time series results	23/30	12/30	3/30	11/30	

Results are not adjusted to multiple hypothesis testing

Table 3.2: Time series regression estimates; Test of homogeneity; Test of Full insurance

			Time series estimates				Test of homogeneity			Test of Full Insurance			
State_num	Village name	# of HHs	Beta		Xi		LR test that Betas are equal			Test if Beta=1	Test if Xi=0	Joint Test if Beta=1&Xi=0	
			mean	sd	mean	sd	chi2	df	pvalue	pvalue	pvalue	HotellingF-stat	pvalue
OR1	Ainlatunga	38	0.740	0.580	0.134	0.448	127.26	37	0.000	0.009	0.074	6.07	0.005
BH1	Arap	35	0.723	0.553	0.035	0.229	52.67	34	0.021	0.006	0.377	6.74	0.004
AP1	Aurepalle	61	0.914	0.643	0.044	0.150	182.55	60	0.000	0.301	0.027	2.99	0.058
GJ1	Babrol	39	0.958	0.516	0.008	0.037	192.10	38	0.000	0.618	0.199	0.94	0.401
KN1	Belladamadugu	40	0.509	0.504	0.056	0.175	35.07	39	0.650	0.000	0.049	20.21	0.000
BH2	Bhagakole	31	0.820	0.495	0.011	0.079	80.99	30	0.000	0.052	0.431	2.19	0.130
OR2	Bilaikani	35	0.901	0.493	0.037	0.294	234.21	34	0.000	0.242	0.465	0.73	0.489
OR3	Chandrasekharpur	40	0.862	0.619	0.315	1.921	168.02	39	0.000	0.165	0.306	1.36	0.269
GJ2	Chatha	37	0.906	0.817	0.031	0.062	357.97	36	0.000	0.486	0.004	4.66	0.016
AP2	Dokur	40	0.653	0.693	0.040	0.120	70.67	39	0.001	0.003	0.044	5.26	0.010
JH1	Dubaliya	40	0.792	0.887	0.019	0.090	143.71	39	0.000	0.146	0.198	3.19	0.052
JH2	Dumariya	39	0.615	0.523	0.092	0.149	31.45	38	0.765	0.000	0.000	17.92	0.000
JH3	Durgapur	38	0.537	0.563	-0.203	2.669	46.22	37	0.142	0.000	0.641	12.68	0.000
JH4	Hesapiri	39	1.096	2.609	0.016	0.430	405.77	38	0.000	0.819	0.817	0.37	0.695
BH3	Inai	28	0.707	0.723	0.100	0.212	93.15	27	0.000	0.041	0.019	4.17	0.027
AP3	JCAgraharam	37	0.521	0.561	0.007	0.037	39.50	36	0.317	0.000	0.295	13.59	0.000
MH1	Kalman	61	0.801	0.583	0.016	0.076	115.51	60	0.000	0.010	0.105	4.76	0.012
MH2	Kanzara	62	0.752	0.557	0.026	0.111	96.52	61	0.003	0.001	0.072	7.30	0.001
KN2	Kapanimbargi	41	0.772	0.563	0.046	0.149	177.25	40	0.000	0.013	0.054	5.10	0.011
GJ3	Karamdichingariya	37	0.854	0.464	0.008	0.024	91.16	36	0.000	0.063	0.039	3.10	0.058
MH3	Kinkhed	48	0.852	0.550	0.014	0.053	105.58	47	0.000	0.069	0.070	2.93	0.064
GJ4	Makhiyala	39	0.765	0.573	0.005	0.038	95.70	38	0.000	0.014	0.426	3.36	0.046
KN3	Markabbinahalli	40	0.702	0.825	0.034	0.155	138.16	39	0.000	0.028	0.171	3.11	0.056
AP4	Pamidipadu	39	0.623	0.567	0.008	0.043	58.47	38	0.018	0.000	0.282	8.52	0.001
MP1	Papda	40	0.849	1.044	0.110	0.227	236.80	39	0.000	0.366	0.004	4.58	0.016
MP2	RampurKalan	39	0.806	0.442	0.046	0.117	65.46	38	0.004	0.009	0.018	5.62	0.007
MH4	Shirapur	88	0.932	0.434	0.018	0.112	242.33	87	0.000	0.148	0.136	2.05	0.135
OR4	Sogar	39	0.629	0.552	0.043	0.269	40.66	38	0.354	0.000	0.321	9.52	0.000
BH4	Susari	30	0.856	0.595	0.043	0.198	121.75	29	0.000	0.195	0.247	1.49	0.244
KN4	Tharati	41	0.836	0.624	0.034	0.085	137.40	40	0.000	0.100	0.016	4.14	0.024
	Pooled	1261	0.785	0.761	0.038	0.598	3559.05	1260	0.000	0.000	0.023	51.42	0.000

Table 3.3: Heterogeneity Bias test and Heterogeniety Robust Test

			Bias test	Heterogeneity robust		
State_num	Village	Std Test	Interaction	Risk	Time	Risk &Time
OR1	Ainlatunga	0.030**	0.684	0.028*	0.030**	0.028*
		(0.015)	(0.493)	(0.014)	(0.015)	(0.015)
BH1	Arap	0.015**	0.610	0.015**	0.016**	0.015**
		(0.007)	(0.882)	(0.007)	(0.008)	(0.008)
AP1	Aurepalle	0.009***	1.374***	0.007**	0.011***	0.008**
		(0.003)	(0.501)	(0.003)	(0.003)	(0.003)
GJ1	Babrol	0.008*	1.813**	0.005	0.008*	0.006
		(0.005)	(0.916)	(0.004)	(0.005)	(0.004)
KN1	Belladamadugu	0.011***	0.439	0.011***	0.011**	0.011**
		(0.004)	(1.064)	(0.004)	(0.004)	(0.004)
BH2	Bhagakole	0.002	4.197***	0.001	0.004	0.002
		(0.003)	(1.464)	(0.003)	(0.003)	(0.003)
OR2	Bilaikani	0.016*	1.233**	0.010	0.016*	0.008
		(0.009)	(0.602)	(0.009)	(0.009)	(0.008)
OR3	Chandrasekharpur	-0.010	0.137	-0.010	-0.005	-0.006
		(0.007)	(0.344)	(0.007)	(0.006)	(0.006)
GJ2	Chatha	0.002	-0.225	0.004	-0.003	0.000
		(0.008)	(0.368)	(0.008)	(0.008)	(0.007)
AP2	Dokur	0.006	-0.172	0.006	0.008*	0.008*
		(0.005)	(0.978)	(0.004)	(0.004)	(0.004)
JH1	Dubaliya	0.021*	0.510	0.020*	0.022	0.019
		(0.011)	(0.903)	(0.011)	(0.014)	(0.014)
JH2	Dumariya	0.036***	-0.183	0.036***	0.033***	0.033***
		(0.011)	(0.697)	(0.011)	(0.010)	(0.010)
JH3	Durgapur	0.004	0.726*	0.002	0.004	0.002
		(0.003)	(0.388)	(0.002)	(0.002)	(0.002)
JH4	Hesapiri	0.079***	0.674**	0.065***	0.073***	0.063***
		(0.029)	(0.296)	(0.024)	(0.027)	(0.024)
BH3	Inai	0.043***	1.090*	0.037***	0.045***	0.040***
		(0.016)	(0.625)	(0.014)	(0.016)	(0.014)
AP3	JCAgraharam	0.005**	0.214	0.005**	0.005**	0.005**
		(0.002)	(1.275)	(0.002)	(0.002)	(0.002)
MH1	Kalman	0.003	-0.774	0.003	0.002	0.003
		(0.003)	(0.736)	(0.002)	(0.002)	(0.002)
MH2	Kanzara	0.008***	1.119	0.008***	0.007**	0.006**
		(0.003)	(1.318)	(0.003)	(0.003)	(0.003)
KN2	Kapanimbargi	0.018***	1.821**	0.015***	0.021***	0.017***
		(0.004)	(0.760)	(0.004)	(0.004)	(0.004)
GJ3	Karamdichingariya	0.003***	4.493	0.003**	0.003***	0.003**
		(0.001)	(2.803)	(0.001)	(0.001)	(0.001)
MH3	Kinkhed	0.019***	0.021	0.019***	0.021***	0.021***
		(0.004)	(0.780)	(0.004)	(0.004)	(0.004)
GJ4	Makhiyala	-0.001	0.098	-0.001	-0.004**	-0.004**
		(0.002)	(1.271)	(0.002)	(0.002)	(0.002)
KN3	Markabbinahalli	0.010***	0.332	0.009***	0.010***	0.009***
		(0.003)	(0.626)	(0.003)	(0.003)	(0.003)
AP4	Pamidipadu	0.009**	1.567*	0.008*	0.008*	0.006
		(0.004)	(0.947)	(0.004)	(0.004)	(0.004)
MP1	Papda	0.013***	-0.932	0.013***	0.011***	0.012***
		(0.004)	(0.792)	(0.004)	(0.004)	(0.004)
MP2	RampurKalan	0.017***	-0.850	0.017***	0.015***	0.016***
		(0.004)	(1.320)	(0.004)	(0.004)	(0.004)
MH4	Shirapur	0.002	0.027	0.002	0.001	0.001
		(0.002)	(0.353)	(0.002)	(0.002)	(0.002)
OR4	Sogar	0.014***	0.844	0.014***	0.013***	0.012**
		(0.005)	(0.724)	(0.005)	(0.005)	(0.005)
BH4	Susari	0.004	0.477	0.002	0.001	-0.001
		(0.011)	(0.345)	(0.010)	(0.009)	(0.008)
KN4	Tharati	0.011***	1.103	0.010**	0.012***	0.010**
		(0.004)	(0.985)	(0.004)	(0.004)	(0.004)
	Pooled	0.009***	0.674***	0.008***	0.009***	0.008***
		(0.001)	(0.169)	(0.001)	(0.001)	(0.001)

Table 3.4: Association between demographics and estimated HH parameters (N=1261)

	Risk Tolerance $\hat{\beta}_i$	Time preference $\hat{\log \eta_i}$	Pareto Weight $\hat{\log \rho_i}$
Household Composition			
Number of Adult Male	-0.085***	-2.549	672.873
	(0.028)	(1.918)	(400.386)
Number of Adult Female	-0.005	0.327	-62.525
	(0.026)	(1.285)	(218.799)
Number of Children (< 12 yrs)	-0.043***	-1.907***	33.811
	(0.015)	(0.567)	(90.531)
Number of Elders (> 60 yrs)	-0.036	0.645	306.158
	(0.030)	(2.062)	(255.200)
Number of members outside the HH	-0.010	0.421	-294.475**
	(0.013)	(0.827)	(137.353)
Household head characteristics			
Education (in yrs)	0.010*	-0.260	59.277
	(0.005)	(0.507)	(50.086)
Gender (male=1)	0.166**	1.707	679.077
	(0.070)	(5.119)	(792.431)
Age	0.001	-0.024	10.698
	(0.002)	(0.125)	(13.970)
Wealth proxy			
Total land area holding	0.008	0.610	-80.667
	(0.006)	(0.544)	(59.814)
Expenditure Quintile (1=Poorest)	0.169***	-2.945***	-221.450
	(0.021)	(1.048)	(146.493)
Constant	0.256**	-4.224	710.607
	(0.117)	(7.614)	(845.706)

The table reports the association between demographic variables and household's estimated tolerance, time preference and pareto weights. Unit of observation is household. Village fixed effects are included in each estiamtion. Standard errors in paranthesis are clustered at village level. * p<0.10 ** p<0.05 *** p<0.01.

CONCLUSION

This thesis examines the role of social safety nets in providing food security and income stability in developing economies. The first chapter examines the impact of a large safety net program on the labor market. The second chapter analyzes the effect of the safety net program on food security. The third chapter asks whether households fully smooth consumption in the face of fluctuations in income.

The first two chapters examine the effectiveness of one of the world's largest safety net program - India's Public Distribution System (PDS). The PDS is by far India's most important safety net, providing assistance to over 800 million people and accounting for 60% of the social assistance budget. The empirical analysis exploits changes in the generosity of this transfer brought about by India's National Food Security Act (NFSA) in 2013. This policy variation is combined with household and individual-level data from ICRISAT's VDSA panel between 2010 and 2015.

In the first chapter, we show that increased PDS transfers led to lower labor supply and higher wages, and that these general equilibrium effects are significantly welfare improving for poor households, especially the poorest quintile. These results are highly relevant for policy as they imply that the labor market effects further strengthen the pro-poor targeted objective of the PDS program. In addition, as these general equilibrium effects are stronger when households face adverse productivity shocks, our results suggest that the PDS program can play an important role in preventing the vicious cycle of high labor supply and low wages that afflicts poor households in bad years. Our results also highlight the importance of accounting for local general equilibrium effects. Ignoring these labor market effects would lead us to underestimate the impact of PDS program on the welfare of the poor.

In the second chapter, we show that increased PDS subsidies substantially improved nutrition. In particular, PDS subsidies "crowded- in" consumption of diverse food items, and consequently increased food consumption in terms of quantities and total calorie, protein and fat intake. Our results suggest that households reduce market purchase of staple cereals and use the extra saving to purchase more nutritious food such as pulses, milk and milk products, fruits and vegetables. These results imply that PDS provides more flexibility in consumption patterns for beneficiary households, who benefit not only from the provision of subsidized cereal but also in terms of overall food intake. Furthermore, we find that PDS beneficiaries consume 84% of the subsidy's transfer value in the form of food, suggesting that the transfer does not cause them to substantially reduce their expenditures on non-subsidized food. We argue that intra-household bargaining may explain these results, as we find that households where women decide on resource allocations spend greater proportion of their PDS transfer value on food expenditures.

These results have important implications for the Indian policy debate around the effectiveness of the NFSA and the PDS program. The PDS has been criticized on the grounds that the program is poorly targeted, does not reach the intended beneficiaries and hence may have little impact on nutrition. Furthermore, critics contend that PDS encourages only "empty calories", and thus may crowd-out more nutritious food items and not improve dietary diversity (Desai and Vanneman, 2015; Gulati et al., 2012). Our results suggest that these criticisms are not generally valid. Given the constraints of our study area, our results show that the NFSA and state-level PDS initiatives effectively reached the intended beneficiaries and had a positive impact on household nutrition. Morever, the PDS has also been criticized on the grounds that the program makes beneficiaries "lazy" (Madras High Court, quoted in the Telegraph India (2018)). However, we show that increased PDS transfers led to only a moderate decrease in labor supply and an increase in the equilibrium wage. More importantly, this wage increase particularly benefited the poor, as they are the largest sellers of labor.

As an alternative to PDS, many policy makers have suggested a replacement of PDS with cash transfers. Although in theory, cash transfers are more efficient, the PDS has an intricate political economy in reform that garners huge political support and is often featured in election manifestos. As a consequence, many state governments have focused on improving the efficiency of the PDS program and have refrained from any form of replacement and no state government in India has showed interest in replacing PDS with cash transfers. Only three union territories, administered by the central government, implemented direct benefit transfer program on a pilot basis starting in September 2015. However, preliminary assessments suggest that implementation quality remains an issue (only 65-67% of beneficiaries reported received cash benefits) and that it costs beneficiaries more to collect their cash benefits than collecting food rations (Muralidharan et al., 2017).

In light of the debate over the effectiveness of PDS, our results suggest that, PDS can lead to large improvements in welfare for poor households. The general equilibrium effects on the labor market further strengthen the pro-poor targeted objective of the PDS program. Therefore, despite its inefficiencies, PDS is an effective tool in addressing household nutrition in India and any replacement of the PDS program demands careful consideration.

APPENDIX A

CHAPTER 1

A.1 Figure and Tables

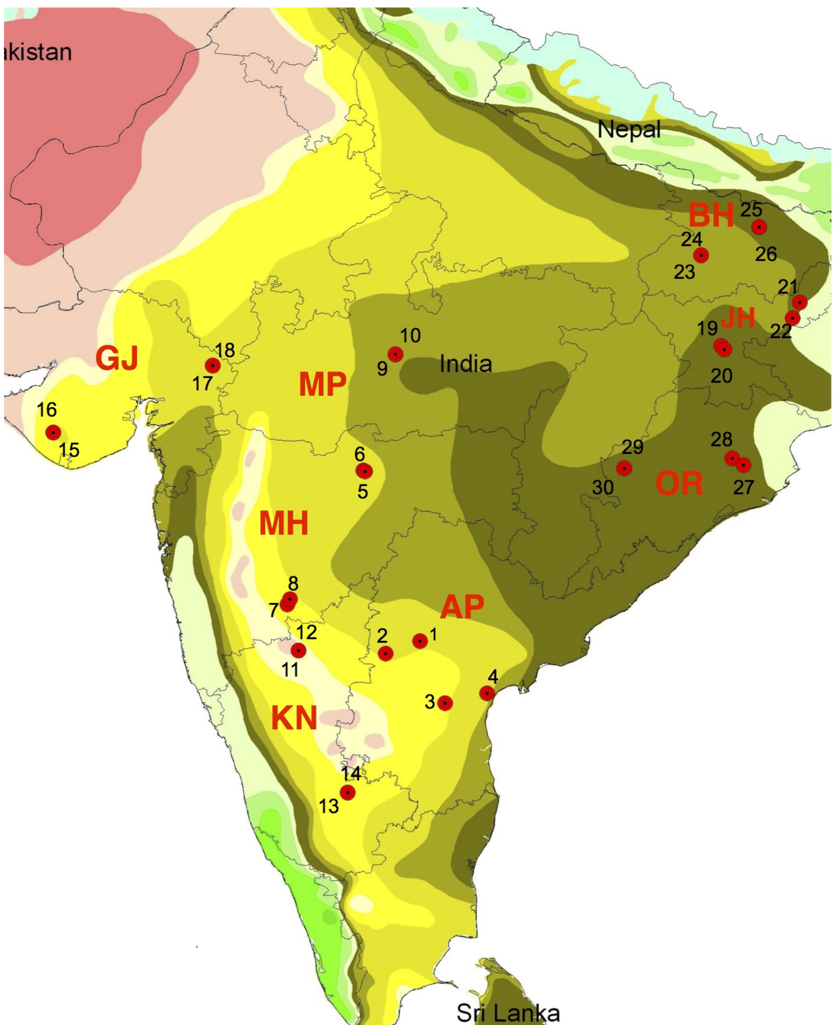


Figure A.1: Location of ICRISAT VDSA villages - 30 villages across 8 states

Table A.1: Monsoon Onset and alternative rainfall shock variables (N=180)

	Rainfall quantity during rainy season	Total rainfall quantity over the year	Rainfall Index	Rainfall Shock
Monsoon Onset	-3.521***	-4.181***	-0.005***	-0.012***
	(1.152)	(0.923)	(0.002)	(0.003)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Rainfall index is percentage deviation from long term average levels in the main rainy season relevant for consumption data (ratio of current year rainfall over long-run mean). Rainfall Shock (as defined in Jayachandran (2006)) =1 if RF > 80th percentile and =-1 if RF< 20th percentile

Table A.2: Effect of Monsoon Onset on Yield and Production

		N=70410			
	Yield	Production Qty	Sold Qty	Market price	N
Rice	-0.840	-1.748*	-4.272**	0.024*	69719
	(0.899)	(0.870)	(1.830)	(0.013)	
Wheat	-1.599***	-7.308**	-1.858	0.006	69719
	(0.579)	(3.301)	(1.861)	(0.005)	
Staple Cereal	-2.182**	-4.068**	-6.602***	0.015*	69719
	(0.989)	(1.906)	(2.343)	(0.008)	
Pigeonpea	-0.239	-1.618	-1.160	-0.013	63245
	(0.758)	(1.190)	(0.712)	(0.034)	
Pulses	-0.272	-0.526	-1.630	0.009	67087
	(0.579)	(0.339)	(2.069)	(0.030)	
Coarse	-0.686	2.664	0.227	-0.019**	49491
	(0.616)	(1.933)	(1.522)	(0.007)	
Food	-0.832	-0.405	2.177		
	(0.584)	(0.370)	(1.632)		
Cash	32.021	-5.756	-3.396		
	(23.009)	(3.641)	(2.021)		
Crop total	16.171	-7.276	-2.171		
	(14.155)	(4.454)	(1.659)		

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coeffcient estimate is from a separate regression with monsoon onset as the regressor and village-average production shocks as outcome variables. In calculating village average yield, production and sold quantity, households with 100% irrigation are left out

Table A.3: Average effects of PDS subsidy and monsoon onset on household labor supply (N=68910)

	Men		Women		Total	
	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset
Total Labor Supply	-0.023**	0.021*	-0.011**	0.021*	-0.034***	0.041**
(Own +Market)	(0.009)	(0.011)	(0.005)	(0.010)	(0.012)	(0.019)
Segregated results:						
Market Labor supply total	-0.022**	0.009	-0.010**	0.015	-0.032**	0.024
(Farm+Non-farm)	(0.010)	(0.010)	(0.005)	(0.010)	(0.013)	(0.017)
Farm	-0.004	0.002	-0.008***	0.005	-0.011*	0.009
	(0.005)	(0.004)	(0.002)	(0.009)	(0.006)	(0.012)
Non-farm	-0.018***	0.007	-0.002	0.009	-0.020**	0.016
	(0.006)	(0.009)	(0.004)	(0.008)	(0.008)	(0.015)
Own Labor supply total	-0.005	0.022**	-0.002	0.013*	-0.008	0.035**
	(0.004)	(0.009)	(0.003)	(0.007)	(0.007)	(0.014)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each set of coefficient estimates is from a separate regression with PDS subsidy value, monsoon onset and their interaction as the regressor variables, row and column headings together describe the outcome variables.

Table A.4: Average effects of PDS subsidy and monsoon onset on village daily wages (N=68265)

	Men		Women		Total	
	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset	PDS Subsidy	Monsoon onset
Total Wage rate	0.3453	-0.0132	0.3250	-0.0279	0.3429	0.0193
	(0.2623)	(0.1378)	(0.1970)	(0.1431)	(0.2702)	(0.1182)
Farm	0.2763	-0.0189	0.3398*	-0.0578	0.2898	-0.0399
	(0.1926)	(0.1128)	(0.1845)	(0.1407)	(0.1785)	(0.1264)
Non-farm	0.4242	-0.1394	0.4250	0.2726	0.2121	-0.0208
	(0.5855)	(0.1636)	(0.2618)	(0.2316)	(0.2995)	(0.1863)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each set of coefficient estimates is from a separate regression with PDS subsidy value, monsoon onset and their interaction as the regressor variables, row and column headings together describe the outcome variables.The estimations on Non-farm wages of women have 56223 observations.

A.2 Variation in monsoon onset

The ICRISAT data has substantial variation in both rainfall and PDS transfer value, meeting the critical data requirements to identify the buffer effect of PDS.

Figure A2 and A3 show graphs of deviations in annual monsoon onset for all the 30 villages during the study period 2010-15. In figure A3, all the 30 villages are marked on the X-axis, with SAT villages on the left and East India villages on the right. As shown in Figure A2, in a particular village, the monsoon onset is more delayed in certain years (temporal variation). Most villages experienced a delayed monsoon during 2012 and 2014, and an early monsoon in 2013. For instance, in Bhagakole village in Bihar (BH-3 in Figure A3), monsoon arrived ahead by 22 days in 2013, but was delayed by 12 days in 2012 and 2014, relative to their local average. Similarly, in any particular year, the monsoon onset may be more delayed in some villages (cross-sectional variation). As villages in the data are spread across different geo-climatic regions (shown in Figure A1), there is significant variation in the onset of monsoon between villages in a particular year relative to the local average. As shown in Figure A3, villages in Karnataka, Gujarat, Maharashtra and Jharkhand experienced substantial deviations in monsoon onset. For instance, in 2014, monsoon onset in Shirapur and Kanzara villages in Maharashtra was delayed by 58 days and 32 days in comparison to monsoon that arrived ahead by 10 and 15 days in Makhilaya and Karamdichingariya villages in Gujarat, all relative to their local average.

In conjunction with rainfall, the ICRISAT data has considerable spatial and temporal variation in PDS subsidy value. In a particular month, BPL households in certain states were exposed to a more generous PDS subsidy than the average BPL household in our sample (cross-sectional variation). For instance, in 2014, PDS subsidy value for BPL households in Jharkhand was about 2.3 times greater than in Gujarat. Similarly for BPL households in certain states, PDS value increased after 2013 (temporal variation). For instance, PDS subsidy value in Karnataka increased by about 75% in June 2013. The spatial and temporal in PDS subsidy value are clearly depicted in Figure 1. After 2013, PDS subsidy value increased in Karnataka, Maharashtra, Bihar and Madhya Pradesh; whereas it did not change in Gujarat, Jharkhand and Orissa. In addition, the increase in PDS subsidy value was greater in Karnataka as compared to Madhya Pradesh or Andhra Pradesh. For the sake of interpretation, let the time period before and after 2013 be referred to as pre and post-NFSA and suppose the villages can be grouped into two sets - with and without PDS expansion. Figure A4 shows the distribution of the monsoon onset deviations from local average, across the four identified cells - Pre and Post NFSA, and With and without Expansion. The histogram shows that the distribution of monsoon onset deviation is similar across pre and post NFSA years for both set of villages (with and without PDS expansion) and hence forms the rationale for our identification strategy.

A.2.1 Triple difference design

The triple difference approach compares, among villages with similar rainfall, villages that were exposed to a more generous PDS program with villages that were exposed to a less generous PDS program. Consider two pairs of villages V1-V2 and V3-V4 in two time periods T1 and T2 and one of the villages in each pair, say V2 and V4, is exposed to a generous PDS expansion in T2. Suppose the village pairs face different rainfall shocks, say V1-V2 face an early monsoon and V3-V4 face a late monsoon in both time periods. A standard difference-in-difference comparison of before and after PDS expansion within each pair would give the impact of PDS expansion during an early monsoon onset (for pair V1-V2) and during a late monsoon onset (for V3-V4). The difference between these difference-in-differences estimates would give the triple-difference estimate.

For example, Figure A5 shows three examples of two village pairs. In each example, one of the village pair faced a late monsoon onset whereas another pair faced an early monsoon in 2014. Furthermore, within each pair, one of the villages was exposed to a more generous PDS expansion whereas the other village was either exposed to a less generous PDS expansion (Example 3) or no PDS expansion (Examples 1 and 2). For instance, in example 1, the pair - Babrol village in Gujarat and Bhagakole in Bihar - experienced delayed monsoons in 2012 and 2014 and an early monsoon in 2013. However, in 2014, Bhagakole was exposed to a more generous PDS expansion under NFSA, but there was no PDS expansion in Babrol. The difference-in-difference estimate between these two villages may be interpreted as the effect of PDS expansion during a late monsoon. Similarly, the other pair - Makhilaya village in Gujarat and Aurepalle in Andhra Pradesh - experienced early monsoons in 2013 and 2014. However, in 2014, Aurepalle was exposed to a more generous PDS program, but there was no expansion in Makhilaya. Accordingly, the difference-in-difference estimate between the latter village pair may be interpreted as the effect of PDS expansion during an early monsoon. The difference between the two village pairs would give the triple difference estimate.

Indeed, a second source of variation is derived from villages with similar PDS expansion and a differential monsoon onset distribution. In this case, the triple difference approach compares, among villages with similar PDS subsidy value, those that experienced a more delayed monsoon with those that experienced a less delayed monsoon. For instance in Example 2 in Figure A5, the village pair - Kanzara and Kinkhed in Maharashtra - were exposed to the same PDS subsidy expansion in 2014; but Kanzara faced a delayed monsoon in 2014 and Kinkhed faced a relatively early monsoon in 2013 and 2014. And the other pair - Chatha in Gujarat and Ainlatunga in Orissa - did not experience any expansion in the PDS subsidy in 2014; but Chatha faced a delayed monsoon and Ainlatunga faced an early monsoon in 2014.

In summary, the interaction between PDS subsidy value and monsoon onset accounts for both the variation in monsoon onset, conditional on PDS subsidy value and the variation in PDS subsidy value, conditional on monsoon onset. A simple triple difference model treats the two sources of variation symmetrically and the interaction term would be the weighted average of both the effects.

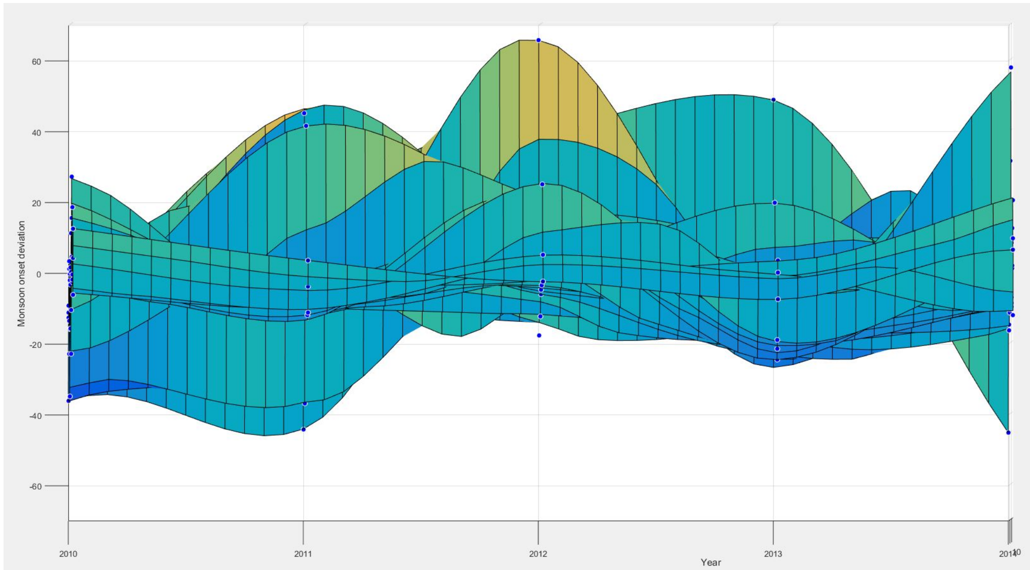


Figure A.2: Monsoon onset deviation, within and between villages, from 2010-2015

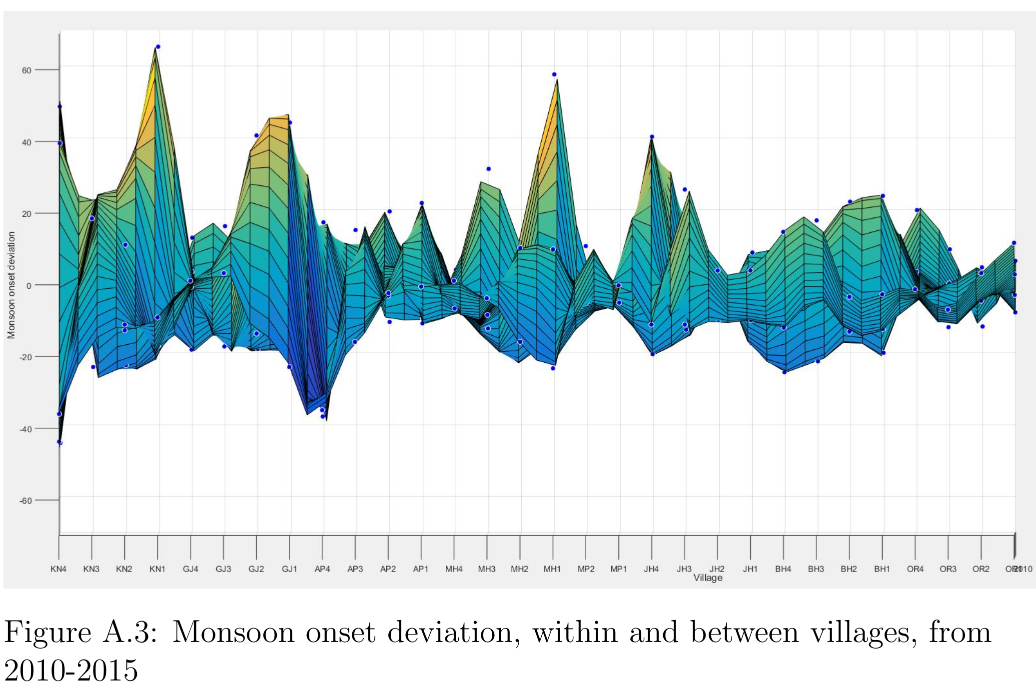


Figure A.3: Monsoon onset deviation, within and between villages, from 2010-2015

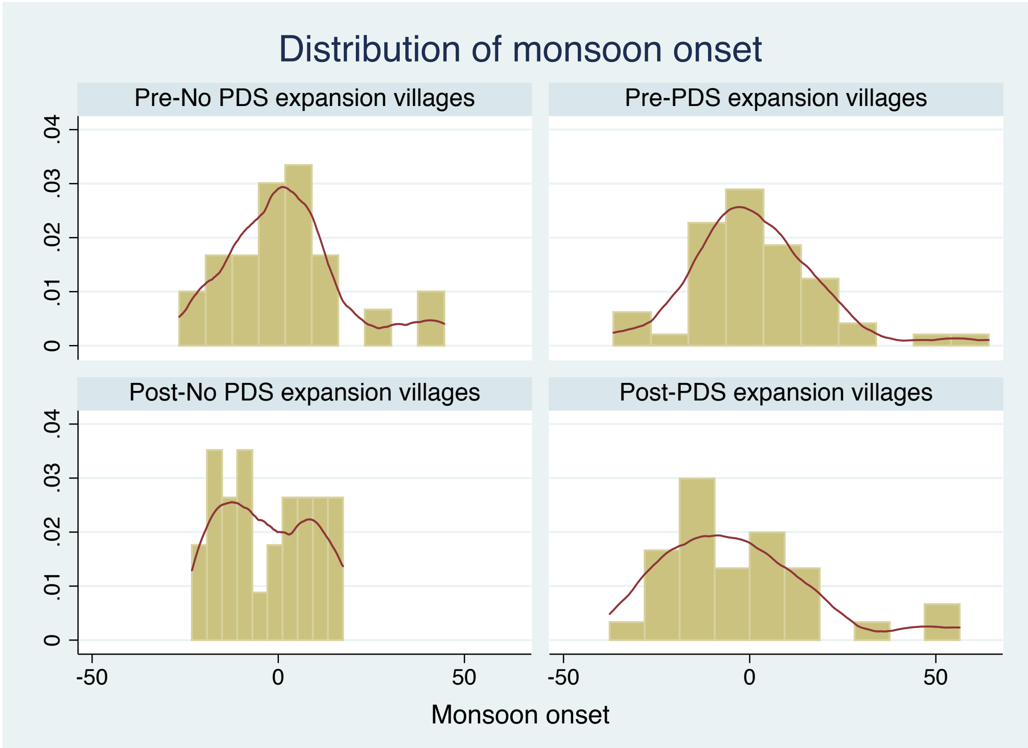


Figure A.4: Histogram of monsoon onset deviation from local average, across 4 cells - Pre and Post, With and without expansion

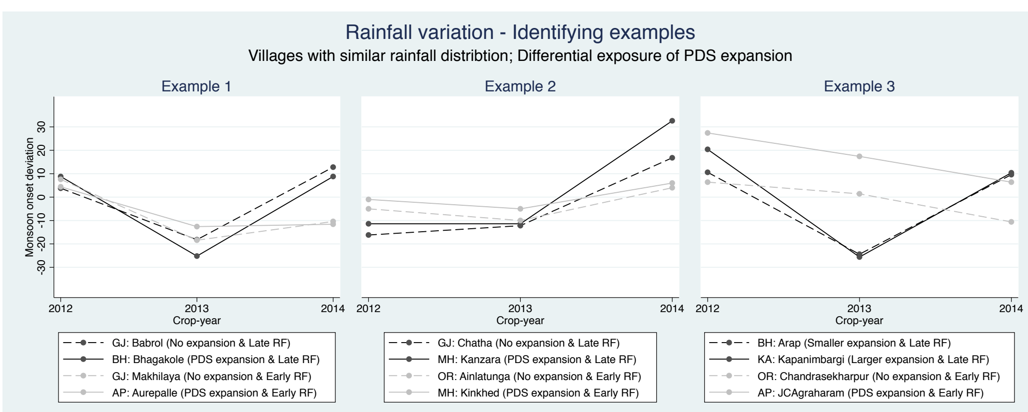


Figure A.5: Villages pairs with similar rainfall; Differential exposure of PDS expansion

APPENDIX B

CHAPTER 2

B.1 Figure and Tables

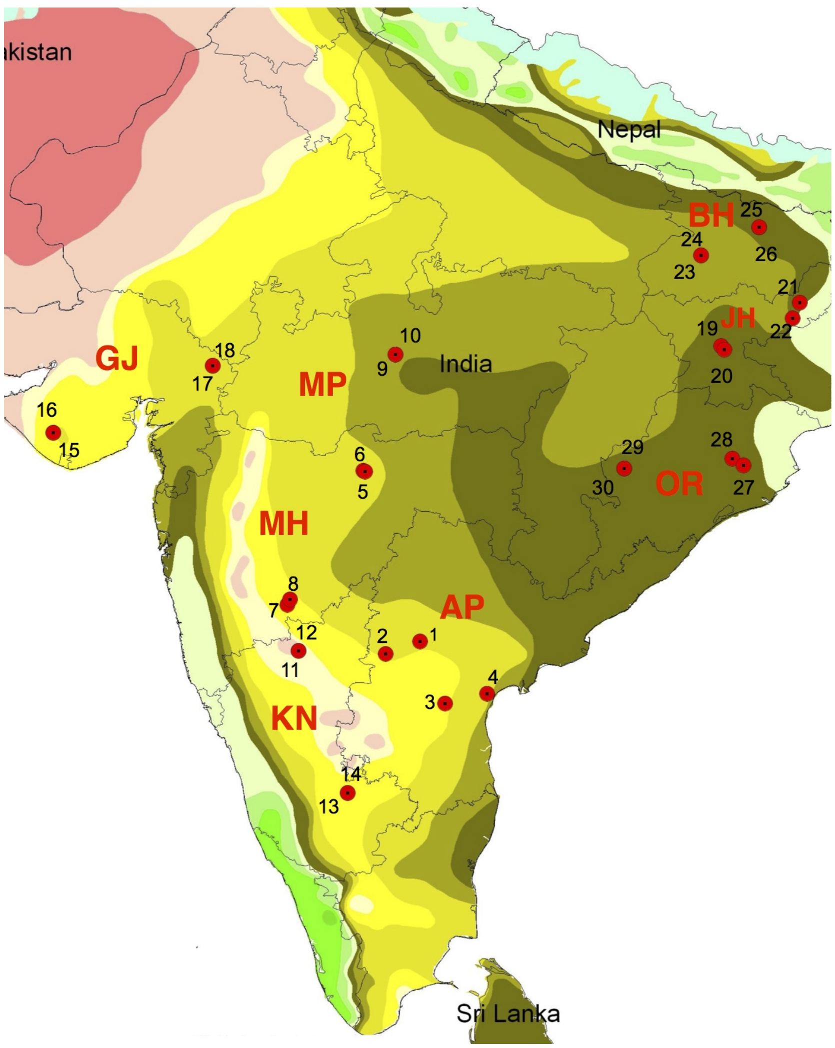


Figure B.1: Location of ICRISAT VDSA villages - 30 villages across 8 states

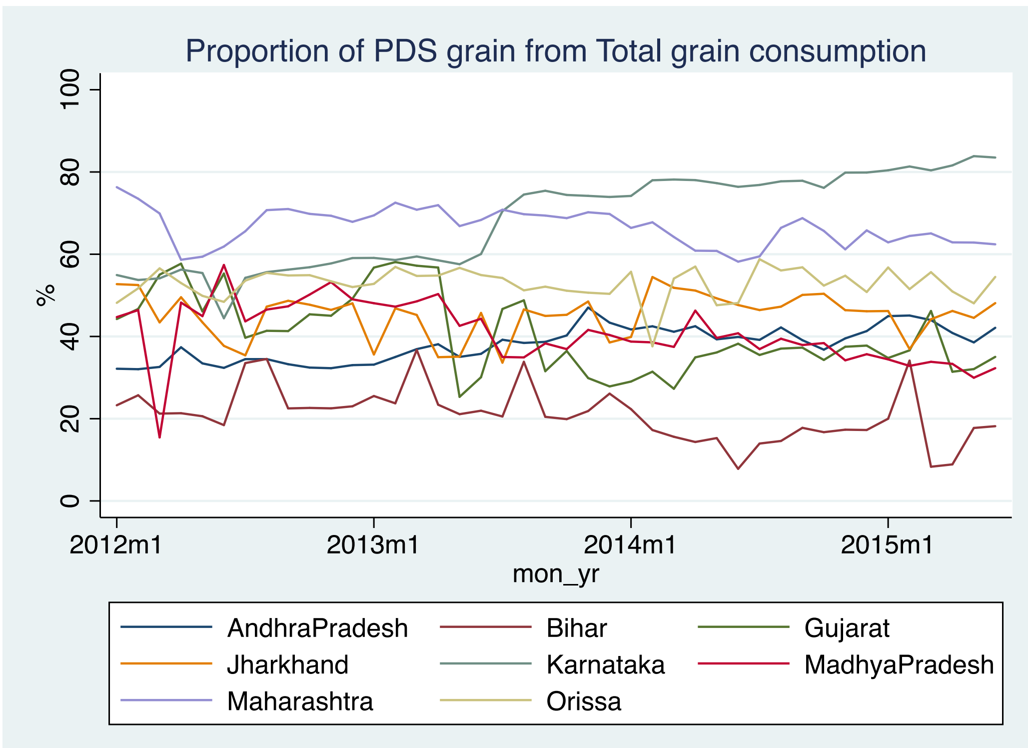


Figure B.2: Proportion of PDS grain out of Total grain consumption, By State

Table B.1: PDS Policy Matrix

		PRE-NFSA (Before 2013)			POST-NFSA (After 2013)			
		Item	Quantity	Price	Quantity	Price	Quantity	Price
					Oct-14		**Apr-15**	
	AAY	Rice	35kg	Rs 2/kg	-	-	-	-
Andhra Pradesh†	BPL	Rice	4kg/member	Rs 2/kg	6kg/member	-	5kg/member	-
			(Max 20kg/HH)		(No ceiling)		(No ceiling)	
		Wheat	No Wheat					
					NFSA - Nov-14			
	AAY	Rice	21kg	Rs 3/kg	-	-		
Bihar		Wheat	14kg	Rs 2/kg	-	-		
	BPL	Rice	15kg	Rs 7/kg	3kg/member	Rs 3/kg		
		Wheat	10kg	Rs 5/kg	2kg/member	Rs 2/kg		
	AAY	Rice	16kg	Rs 3/kg				
		Wheat	19kg	Rs 2/kg				
Gujarat					No changes			
	BPL	Rice	5 kg	Rs 3/kg				
		Wheat	13 kg	Rs 2/kg				
	AAY	Rice	35kg	Re 1/kg				
Jharkhand	BPL	Rice	35kg	Re 1/kg	No changes			
		Wheat	No wheat					
					Anna Bhagya Yojana Jul-13		**Anna Bhagya Oct-13**	
	AAY	Rice	29kg	Rs 3/kg	-	Rs 1/kg	-	Rs 1/kg
		Wheat	6kg	Rs 2/kg	-	Rs 2/kg	-	Rs 1/kg
Karnataka								
	BPL	Rice	4kg/member	Rs 3/kg	27 kg	Rs 1/kg	27 kg	Rs 1/kg
		Wheat	1 kg/member	Rs 3/kg	3 kg	Rs 3/kg	3 kg	Rs 1/kg
			(Max 25kg/HH)		(30kg/HH)		(30kg/HH)	
					NFSA Feb-2014			
	AAY	Rice	15kg or 10kg	Rs 3/kg	-	-		
		Wheat	20kg or 25 kg	Rs 2/kg	-	-		
Maharashtra	BPL	Rice	15kg	Rs 6/kg	2kg/member	Rs 3/kg		
		Wheat	20kg	Rs 5/kg	3kg/member	Rs 2/kg		
					(5kg/member)			
	APL	Rice	5kg	Rs 9.6/kg	-	-		
		Wheat	10kg	Rs 7.2/kg	-	-		
					Jul-13 Mukhyamantri Annapurna Scheme		**Apr-14 NFSA**	
	AAY	Rice	5kg	Rs 3/kg	-	Rs 2/kg	-	-
Madha Pradesh		Wheat	30kg	Rs 2/kg	-	Rs 1/kg	-	
	BPL	Rice	1 to 5kg	Rs 4.5/kg	5kg	Rs 2/kg	1kg/member	Rs 1/kg
		Wheat	15-20kg	Rs 3/kg	20kg	Rs 1/kg	4kg/member	Rs 1/kg
			(Max of 20 kg/HH)				(5kg/member)	
					Feb-13			
	AAY	Rice	35kg	Rs 2/kg	-	Rs 1/kg		
	BPL	Rice	25kg	Rs 2/kg	-	Rs 1/kg		
Orissa		Wheat	No wheat for BPL					
	APL (sometimes)	Wheat	10kg	Rs 7/kg	-	-		

†Andhra Pradesh decreased Rice price to Re. 1/kg in Nov-11

‡ Madhya Pradesh reduced Rice price to Re 1/kg in Feb-14.

Table B.2: Impact of PDS Subsidy on staple cereal consumption (N=36,894)

	Quantity (in grams)	Value (in 2010 Rs)
All sources (Market +PDS+Home)		
Rice	18.033***	-0.006
	(2.377)	(0.021)
Wheat	4.793***	-0.011
	(0.862)	(0.011)
Purchase from PDS only		
Rice	19.379***	-0.031
	(2.680)	(0.020)
Wheat	6.977***	0.012
	(0.805)	(0.007)
Without PDS (Market + Home)		
Rice	-1.336	-0.007
	(1.267)	(0.022)
Wheat	-2.179**	-0.030***
	(0.875)	(0.011)
Purchase from market only		
Rice	-0.379	-0.008
	(1.128)	(0.021)
Wheat	-0.991	-0.012
	(0.727)	(0.010)
From Home production only		
Rice	-0.771	-0.002
	(0.830)	(0.013)
Wheat	-1.314**	-0.019**
	(0.580)	(0.008)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor and different food catogories as outcome variables.

Table B.3: MPC energy and nutrient intake with respect to PDS subsidy value and expenditure (N=36,894)

	Panel A MPC with PDS Subsidy			**Panel B MPC with Expenditure**		
	Energy (Kcal)	Protein (milli gms)	Fat (milli gms)	Energy (Kcal)	Protein (milli gms)	Fat (milli gms)
Staple cereal consumption						
Rice and Wheat from PDS	2.920***	69.087***	6.038***	0.007	0.057	0.011
	(0.232)	(6.393)	(0.479)	(0.007)	(0.174)	(0.017)
Rice and Wheat except PDS	-0.483	-13.419	-1.425	0.089***	2.477***	0.229***
	(0.437)	(11.335)	(1.147)	(0.015)	(0.467)	(0.043)
Other food types						
Pulses	0.227***	15.173***	0.278	0.017***	1.134***	0.104***
	(0.042)	(3.076)	(1.586)	(0.003)	(0.181)	(0.034)
Coarse cereals	0.245	7.794	1.211	0.015***	0.484***	0.143***
	(0.201)	(6.268)	(1.756)	(0.005)	(0.144)	(0.042)
Eggs	0.005	0.379	0.379	0.000***	0.038***	0.038***
	(0.005)	(0.400)	(0.400)	(0.000)	(0.011)	(0.011)
Milk and Milk products	0.201*	7.829*	14.275*	0.017***	0.671***	1.202***
	(0.106)	(3.946)	(7.708)	(0.003)	(0.112)	(0.205)
Oils	0.341**	-0.051	38.137**	0.036***	0.000	4.042***
	(0.152)	(0.031)	(16.853)	(0.005)	(0.000)	(0.590)
Sugar	0.183**	0.046**	-	0.016***	3.994***	3.994***
	(0.084)	(0.021)		(0.003)	(0.757)	(0.757)
Vegetables	0.222**	6.364*	1.629*	0.015***	0.487***	0.085***
	(0.090)	(3.222)	(0.904)	(0.003)	(0.107)	(0.020)
Fruits	0.129***	1.299***	-0.006	0.003***	0.057***	0.013***
	(0.037)	(0.388)	(0.216)	(0.001)	(0.011)	(0.004)
Meat	0.010	2.813	-0.630	0.003***	0.625***	0.081***
	(0.012)	(2.167)	(0.578)	(0.001)	(0.095)	(0.012)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor and different food catogories as outcome variables.

Table B.4: MPC on energy and nutrient intake with respect to total expenditure value (N=36,894)

	Energy (Kcal)	Protein (mg)	Fat (mg)
Total Food	0.212***	6.043***	6.030***
	(0.031)	(0.909)	(0.790)
Staple food (Rice and wheat)	0.093***	2.526***	0.270***
	(0.013)	(0.401)	(0.053)
Non-staple food	0.170***	4.863***	7.259***
	(0.026)	(0.744)	(0.997)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor and different food catogories as outcome variables.

Table B.5: Elasticity of calories, proteins and fats with respect to PDS subsidy value and total expenditure value (N=36,894)

	Panel A Elasticity with PDS subsidy			**Panel B Elasticity with Total Expenditure**			
	Energy (Kcal)	Protein (gms)	Fat (gms)	Energy (Kcal)	Protein (gms)	Fat (gms)	Observations
Staple cereal consumption							
Rice and Wheat from PDS	0.640***	0.635***	0.619***	0.042*	0.045*	0.050*	31205
	(0.070)	(0.071)	(0.076)	(0.022)	(0.023)	(0.027)	
Rice and Wheat except PDS	0.019	0.037	0.056	0.252***	0.254***	0.261***	31310
	(0.126)	(0.118)	(0.113)	(0.033)	(0.033)	(0.033)	
Other food types							
Pulses	0.278***	0.280***	0.197**	0.262***	0.262***	0.268***	36368
	(0.050)	(0.053)	(0.085)	(0.028)	(0.028)	(0.042)	
Coarse cereals	0.217***	0.238***	0.299***	0.166***	0.165***	0.159***	19700
	(0.076)	(0.075)	(0.096)	(0.029)	(0.030)	(0.030)	
Eggs	0.372***	0.372***	0.372***	0.129***	0.129***	0.129***	19122
	(0.095)	(0.095)	(0.095)	(0.020)	(0.020)	(0.020)	
Milk and Milk products	0.269**	0.277**	0.267**	0.249***	0.242***	0.250***	28424
	(0.102)	(0.101)	(0.103)	(0.044)	(0.043)	(0.045)	
Oils	0.245***	-	0.246***	0.248***	0.406***	0.247***	36542
	(0.082)		(0.082)	(0.028)	(0.080)	(0.028)	
Sugar	0.238**	0.238**	0.238**	0.236***	0.236***	0.236***	33802
	(0.089)	(0.089)	(0.089)	(0.031)	(0.031)	(0.031)	
Vegetables	0.388**	0.386**	0.468*	0.294***	0.305***	0.302***	36640
	(0.156)	(0.177)	(0.243)	(0.042)	(0.045)	(0.048)	
Fruits	0.843***	0.632***	0.307	0.357***	0.316***	0.325***	29969
	(0.235)	(0.180)	(0.195)	(0.055)	(0.043)	(0.037)	
Meat	0.178	0.233**	-0.232	0.336***	0.335***	0.363***	24208
	(0.127)	(0.112)	(0.281)	(0.040)	(0.042)	(0.041)	

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression with PDS subsidy value as the regressor and different food catogories as outcome variables.

B.2 PDS Subsidy reaches beneficiaries

We validate whether the NFSA and state-level policy changes were actually implemented and whether the beneficiaries received their full entitlement. We attempt to answer these questions in two ways. First, we describe the implementation of the program through time-series graphs of PDS entitlements vs PDS consumption. As we have longitudinal data, we can trace the PDS consumption at the household level over time. Second, we empirically test the impact of PDS entitlements on PDS consumption in a more rigorous manner using a fixed-effect regression, similar to equation (3.2).

Figures B1 and B2 lay side-by-side the PDS entitlements in Panel A against the actual PDS entitlements received in Panel B. Time-series graphs for PDS quantity for rice, wheat and grain (sum of rice and wheat) are provided in Figures B1a, B1b and B1c respectively. Similarly, graphs for PDS price are provided in Figures B2a, B2b and B2c respectively. Each point in Panel B represents the mean entitlement over all the BPL households in that particular state and month.

A comparison of the graphs in Panels A and B in figures B1 and B2 suggests that PDS consumption quantity and PDS price received seem to follow PDS entitlements; more so for PDS price. The most significant jump in PDS consumption is in Karnataka in June 2013 with the introduction of Anna Bhaghya Scheme. PDS rice consumption almost doubled and PDS rice price received dropped to Re.1/kg in the same month as the enactment of Anna Bhagya Scheme, as shown in figure B1a and B2a respectively. In Madha Pradesh, under the "Mukhyamantri Annapurna Scheme", PDS wheat price drop to Re 1/kg in June 2013 and PDS rice price received drop to Re 1/kg in Feb 2014. Similarly, in Bihar and Maharashtra with the implementation of NFSA, the PDS price for rice and wheat received drop to the level of NFSA price entitlements, as shown in figures B2a and B2b. NFSA in Bihar was enacted in March 2014, but in the data the changes in PDS consumption show up only after June 2014. After the adoption of NFSA in Bihar, PDS consumption of rice and wheat significantly increase, as shown in figure B1c. Even for states without any changes in the PDS program, PDS consumption and PDS price received closely follows entitlement. PDS rice consumption hovers around the statutory entitlement of 35kg and 30kgs in Jharkhand and Orissa respectively, as shown in Figure 5a. Similarly, PDS rice price drifts around Re 1 in Jharkhand, Orissa and Andhra Pradesh, as shown Figure B2a. In summary, the graphs show that PDS take-up is high and that the intended beneficiaries receive a significant proportion of their entitlements. But, as the graphs in Panel B are only an approximation, we further examine the take-up of PDS subsidy using a more rigorous fixed effects regression.

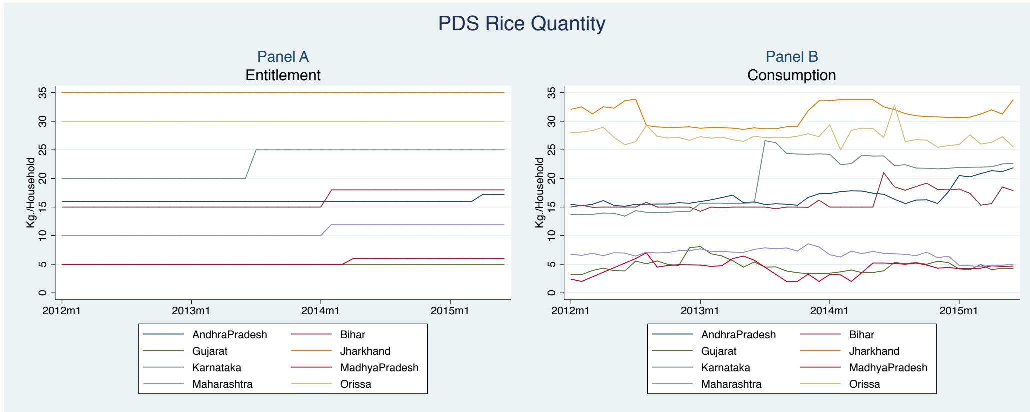
PDS consumption is regressed on PDS quantity entitlements, separately for rice, wheat and grain (rice and wheat). PDS price received, is analyzed similarly. Table 2 presents the results of the fixed effects regressions. The coefficient estimates on the entitlements, interpreted as the proportion of PDS quantity and price entitlement received[1], are reported in Panel A and Panel B respectively. For PDS rice, about 59% of the quantity entitlement and 79% of the price entitlement is received by the intended beneficiaries; for PDS wheat, about 46% of the quantity entitlement and 98% of the price entitlement is received; and for rice and wheat together, 55% of the quantity entitlement and 83% of the price entitlement is received by the intended beneficiaries.

The fixed effects regression results reveal some interesting findings. First, PDS price received is more compliant than PDS quantity. Low pass-through from PDS entitlement to actual consumption could be due to both demand and supply side factors. Khera (2011a) argues that supply side constraints are more relevant for PDS. Based on our field visits in the ICRISAT villages, it is more likely that the low-pass through may be due to supply side factors such as leakage in the PDS supply chain, in providing a consistent delivery of grains to the PDS ration shops, or diversion of grains to the market; and less likely due to demand side factors such as tastes. Second, more PDS rice entitlement reaches households than PDS wheat. This is consistent with previous studies that report that there is more leakage and diversion of grains in PDS wheat Khera (2011b). The results may also reflect the improved efficiency of PDS rice schemes in Karnataka, Jharkhand, Orissa and Andhra Pradesh.

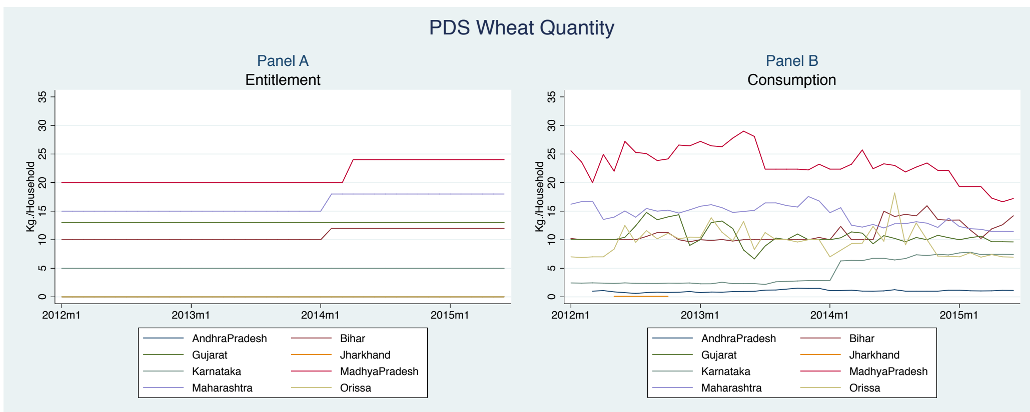
In summary, the graphs in figures B1 and B2 and the fixed effects results, suggest that 55 to 83% of the PDS entitlement reaches the intended beneficiary. Hence, these results validate that the state-level PDS programs and

[1]Previous studies have referred to the ratio of entitlement to consumption as purchase-entitlement ratio Khera (2011b). In this case, the coefficient estimates can be interpreted as the marginal purchase-entitlement ratios

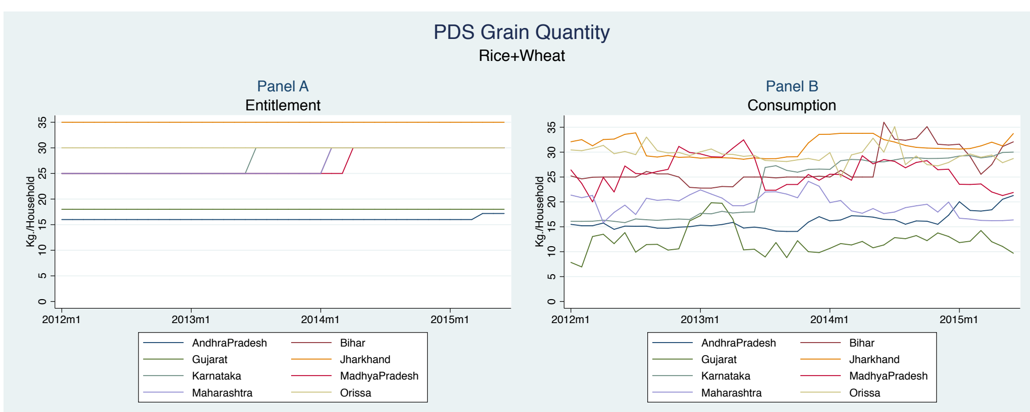
NFSA were actually implemented and reached the intended beneficiaries.



(a) PDS Rice Quantity

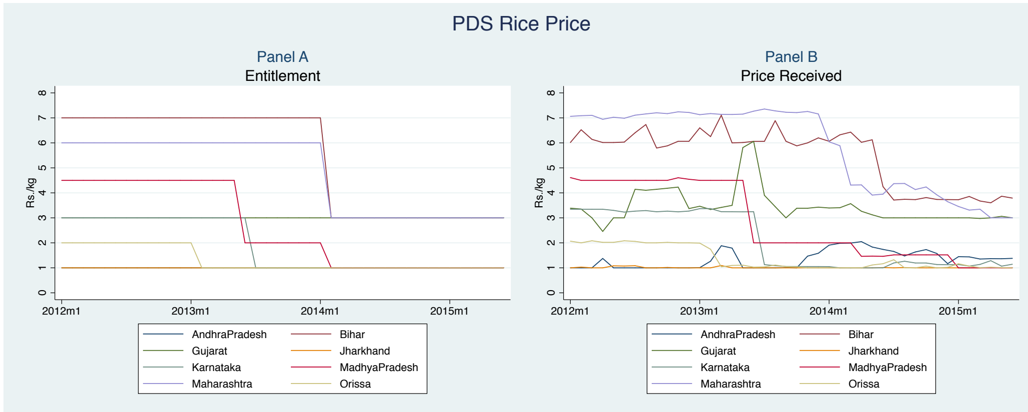


(b) PDS Wheat Quantity

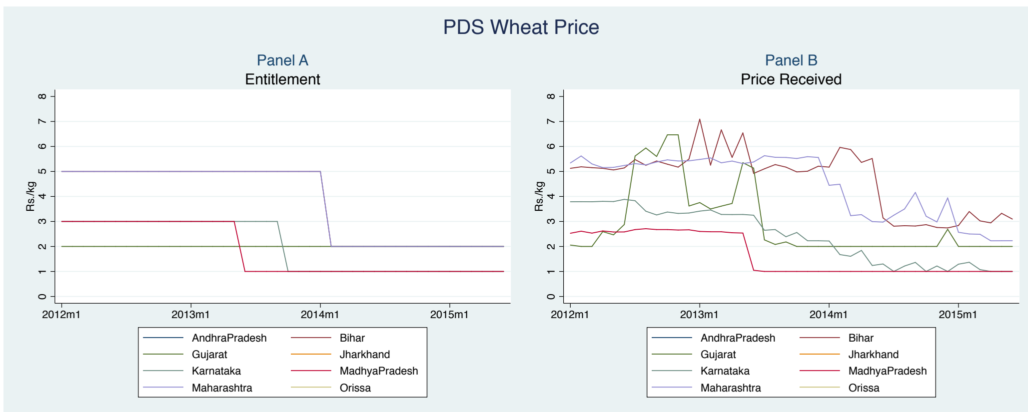


(c) PDS Grain Quantity=PDSRice+ PDSWheat

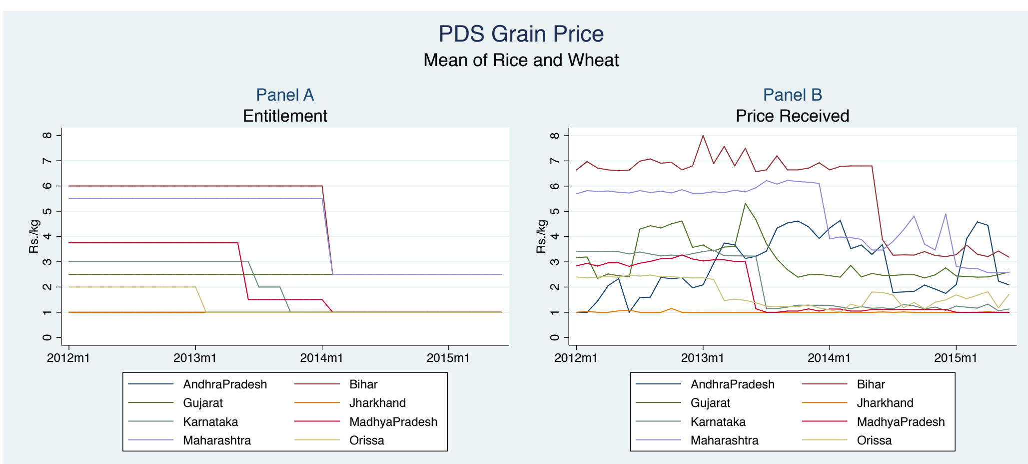
Figure B.3: PDS Quantity Entitlement vs Consumption for BPL households from 2012-15



(a) PDS Rice Price



(b) PDS Wheat Price



(c) PDS Grain Price= Mean of PDS Rice and PDS Wheat

Figure B.4: PDS Price Entitlement vs Consumption for BPL households from 2012-15

Table B.6: PDS Take-up (N=36,894)

	PDS entitlement received
Rice	
Quantity entitlement	0.588***
	(0.096)
Price entitlement	0.795***
	(0.106)
Wheat	
Quantity entitlement	0.464***
	(0.123)
Price entitlement	0.979**
	(0.437)
Staple Cereals (Rice and wheat)	
Quantity entitlement	0.551***
	(0.100)
Price entitlement	0.833***
	(0.171)

Standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. Each coefficient estimate is from a separate regression.

APPENDIX C

CHAPTER 3

C.1 Estimation of Pareto-weight

From (3.12A) we have

$$\frac{\alpha_i}{\beta_i} = \log \eta_i - \frac{1}{N}\sum_{i=1}^{N} \beta_i \log \eta_i \tag{C.1}$$

For any household $i = 1$ and $i = 2$, we have

$$\frac{\alpha_1}{\beta_1} = \log \eta_1 - \frac{1}{N}\sum_{i=1}^{N} \beta_i \log \eta_i$$
$$\frac{\alpha_2}{\beta_1} = \log \eta_2 - \frac{1}{N}\sum_{i=1}^{N} \beta_i \log \eta_i$$

Substituting for $\frac{1}{N}\sum_{i=1}^{N} \beta_i \log \eta_i$ we have

$$\frac{\alpha_1}{\beta_1} = \log \eta_1 - \left[\log \eta_2 - \frac{\alpha_2}{\beta_2}\right]$$
$$\log \eta_2 = \log \eta_1 - \frac{\alpha_1}{\beta_1} + \frac{\alpha_2}{\beta_2}$$

Hence we can express for any household j in terms of i, where $j \neq i$

$$\log \eta_j = \log \eta_i - \frac{\alpha_i}{\beta_i} + \frac{\alpha_j}{\beta_j} \tag{C.2}$$

Substituting (C.2) in (C.1) we get,

$$\begin{aligned}
N\frac{\alpha_i}{\beta_i} &= N\log\eta_i - \left[\Sigma\beta\log\eta_i - \frac{\alpha_i}{\beta_i}\left(\Sigma\beta-\beta_i\right) + \left(\Sigma\alpha-\alpha_i\right)\right] \\
&= (N-\Sigma\beta)\log\eta_i + \frac{\alpha_i}{\beta_i}\left(\Sigma\beta-\beta_i\right) - \left(\Sigma\alpha-\alpha_i\right) \\
&= (N-N\overline{\beta})\log\eta_i + \frac{\alpha_i}{\beta_i}N\overline{\beta} - N\overline{\alpha} \\
\frac{\alpha_i}{\beta_i} &= (1-\overline{\beta})\log\eta_i + \frac{\alpha_i}{\beta_i}\overline{\beta} - \overline{\alpha} \\
(1-\overline{\beta})\log\eta_i &= (1-\overline{\beta})\frac{\alpha_i}{\beta_i} + \overline{\alpha} \\
\log\eta_i &= \frac{\alpha_i}{\beta_i} + \frac{\overline{\alpha}}{1-\overline{\beta}}
\end{aligned}$$

Similarly, from (3.12A) we can derive,

$$\log\rho_i = \frac{\theta_i}{\beta_i} + \frac{\overline{\theta}}{1-\overline{\beta}}$$

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